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Attaining Knowledge Workforce Agility in a Product Life Cycle Environment using Real Options

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ATTAINING KNOWLEDGE WORKFORCE AGILITY IN A PRODUCT LIFE CYCLE ENVIRONMENT USING REAL OPTIONS

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Abstract

The product life cycle (**PLC**) phenomenon has placed significant pressures on high-tech industries which rely heavily on the knowledge workforce in transferring cutting-edge technologies into products. This thesis examines systems where market changes and production technology advances happen frequently and unpredictably during the PLC, causing difficulties in predicting an appropriate demand on the knowledge workforce and in maintaining reliable performance. Knowledge workforce agility (**KWA**) is identified as a desirable means for addressing the difficulties, and yet previous work on KWA is incomplete.

This thesis accomplishes several critical tasks for realizing the benefits of KWA in a representative PLC environment, semiconductor manufacturing. Real options (**RO**) is chosen as the approach towards exploiting KWA, since RO captures the essence of KWA – options in manipulating knowledge capacity, a human asset, or a self-cultivated organizational capability for pursuing interests associated with change. Accordingly, market demand change and workforce knowledge (**WK**) dynamics in adoption of technology advances are formulized as underlying stochastic processes during the PLC. This thesis models KWA as capacity options in a knowledge workforce and develops a RO approach of workforce training, either initial or continuous, for generating options. To quantify the elements of KWA that impact production, the role of the knowledge workforce in production and costs in obtaining KWA are characterized mathematically. It creates necessary RO valuation methods and techniques to optimize KWA.

An analytical examination of the PLC models identifies that KWA has potential to reduce negative impacts and generate opportunities in an environment of volatile demand, and to compensate unreliable performance of knowledge workforce in adoption of technology advances. The benefits of KWA are especially important when confronting highly volatile demand, a low initial adoption level, shrinking PLCs, a growing market size, intense and frequent WK dynamics, insufficient learning capability of employees, or diminishing returns from investments in learning. The thesis further assesses RO, as an agility-driven approach, by comparing it to a chase-demand heuristic and to the Bass forecasting model under demand uncertainty. The assessment demonstrates that the KWA attained from the RO approach, termed RO-based KWA, leads to a stably higher yield, to a persistently larger net present value (**NPV**), and to a NPV distribution that is more robust to highly volatile demand. Subsequently, a quantitative evaluation of KWA value shows that the RO-based KWA creates a considerable profit growth, either with uncertainty in demand or in the WK dynamics. In evaluation, RO modeling and the RO valuation are identified to be useful in creation of KWA value especially in highly uncertain PLC environments. This thesis illustrates the effectiveness of the numerical methods used for solving the dynamic system problem.

This research demonstrates an approach for optimizing KWA in PLC environments using RO. It provides an innovative solution for knowledge workforce planning in rapidly changing and highly unexpected environments. The work of this thesis is representative of studying KWA using quantitative techniques, where there is a dearth of quantitative studies in the literature.

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Commonly Used Acronyms

List of Commonly Used Acronyms

CT	Continuous Training
CTT	The Percent of Labor Time Spent in Continuous Training
DP	Dynamic Programming
GBM	Geometric Brownian Motion
IT	Initial Training
KW	Knowledge Workforce
KWA	Knowledge Workforce Agility
NPV	Net Present Value
PLC	Product Life Cycle
RO	Real Options
WK	Workforce Knowledge

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Chapter 1

Introduction

1.1 Knowledge Workforce Agility Explores A New Frontier

Traditional conditions of stability and predictability are being replaced by the modern conditions of change and unpredictability. This brings many industrial and business organizations great difficulties in the attempt to fulfill development goals. The ability of an organization to effectively overcome the difficulties is often referred to as *agility*.

The lack of agility has been reported as one major reason that many traditional manufacturing solutions could not outpace the increasing rate of change since the 1990's. Agility has gained considerable interest among researchers and industrialists, and it has become one of the leading research topics in the past fifteen years [e.g., Kidd (1994, 1995), Dove (1994, 1995), Youssef (1994), Goldman et al. (1995), Nelson & Harvey (1995), Katayama & Bennett (1999), and Yusuf et al. (1999)]. Although definitions of agility are varied and sometimes vague in the extensive agility research, many would believe agility is a competency that involves actively taking advantages of opportunities and positively countering threats, all of which arise from frequent, large and unpredictable changes. They would also agree that agility facilitates the accomplishment of competitive success through strategically keeping an economical balance among important metrics of change proficiency (e.g., time, cost, robust, and scope of change). The lack of agility may result in significant losses.

Workforce agility, which forms the human facet of an agility framework, is the benefits of agility with respect to workforce [e.g., Weick (1979), Prahalad & Hamel (1990), Kidd (1994), Yusuf et al. (1999), Gunasekaran (1998, 1999), and Breu et al. (2001)]. Knowledge-intensive organizations, for example, high-tech industries, would especially appreciate workforce agility since they rely heavily on workforce capability in transferring cutting-edge technologies into products. Thus, the knowledge workforce should be the real concern in the study of workforce agility. This thesis uses the term *knowledge workforce agility* (**KWA**) to be precise.

A phenomenon termed the *product life cycle* (**PLC**), which has commonly been observed in many high-tech industries, poses demands on KWA. The semiconductor manufacturing industry is representative of these, whose generations of products are characterized with clear PLCs. Demand during a PLC has a bell-shaped pattern [e.g., Rogers (1962), and Bass (1969)]. However, instead of following the pattern exactly, demand often demonstrates a partly stochastic manner as it fluctuates over the PLC [e.g., Bollen (1999), and Bass (2004)]. To manage such demand fluctuations is challenging, and yet it is very important since the sales price drops rapidly during the PLC (called *price erosion*). Thus, production processes are preferred to remain unchanged, so that the production scale can be adjusted to desired levels to meet rapid and unexpected changes in demand. Contrary to the aforementioned reason, to remedy deficiencies caused by the introduction of new generations before production technologies mature, manufacturers have to adopt timely technology advances and modify production processes. The successive process changes during the PLC make the skills or *workforce knowledge* (**WK**) partially lose the relevance to what they attempt to fulfill, causing WK dynamics during the PLC. [e.g.,Hatch & Mowery (1998), Carrillo & Gaimon (2000), Terwiesch & Bohn (2001), and Terwiesch & Xu (2004)]. The individual learning thereby is interrupted frequently and unanticipatedly (of course, the same to the organizational learning). Workforce training efforts have to be changed correspondingly without much delay. The market changes and the production technology advances during the PLC cause a paradox for the knowledge workforce management as the demands on the knowledge workforce and their performance become unstable and unanticipated. KWA exhibits a potential advantage for addressing the paradox.

Without commonly understood business practices or enterprise reference models, a host of things are found to be ambiguous in the attempt to carry out KWA in practices, such as the KWA model, agility-driven mechanisms and algorithms, rewards from KWA and expenses, and the performance measures for KWA. The previous studies of workforce agility are limited, and the most of them still linger at a conceptual level [e.g., Weick (1979), Prahalad & Hamel (1990), Kidd (1994), Plonka (1997), Gunasekaran (1998), Gunasekaran (1999), Yusuf et al. (1999), Breu et al. (2001), and Sumukadas & Sawhney (2004)]. Numerous research and practices of workforce flexibility are available, which seem to have formed a good foundation of workforce agility [see Hopp & Van Oyen (2004)]. However, agility has clearly been distinguished from flexibility in many agility studies [e.g., Kidd (1994), and Dove (1995)]. A major difference between workforce agility and workforce flexibility lies in the attitude they hold towards uncertainty. Workforce agility holds a positive attitude toward uncertainty, and knowledge workforce adjustments are made just ahead of taking advantages of opportunities or of countering threats. Workforce flexibility, however, holds a passive attitude, and it responds to more anticipated contingencies in a pre-designed manner. Thus, the scope of the uncertainty that workforce agility is expected to handle is far beyond the capability of workforce flexibility, as Figure 1.1 demonstrates. Furthermore, after reviewing

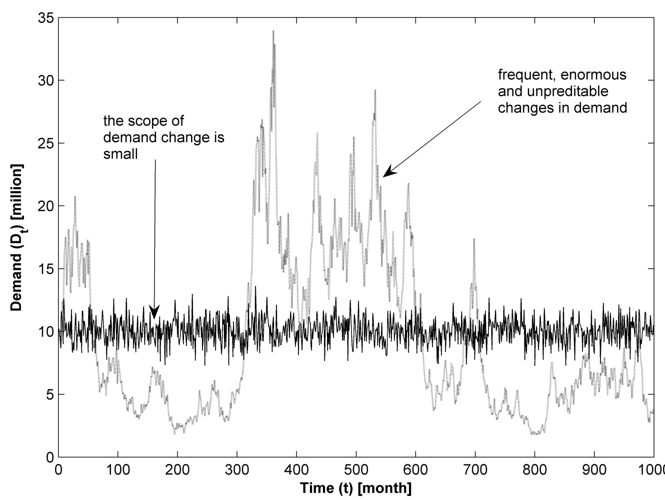


Fig. 1.1. Different Scales of Uncertainty

the canonical policies of workforce flexibility summarized in Hopp & Van Oyen (2004), a very similar impression is attained. That is, that most of these policies have been developed to handle more greatly anticipated contingencies. Therefore, traditional solutions of training and manipulating knowledge workforce under uncertainty could be outmoded or ineffectual in no time in PLC environments. This has already been demonstrated by the work of Nembhard et al. (2002a) and of Nembhard et al. (2005a). They question the reliability in the optimality of traditional workforce flexibility policies in a highly uncertain environment, and *real options* (**RO**) have been shown to be a promising method for remedying the problem. A frontier that workforce flexibility ever could not explore has been identified, whereon an unpreventable evolution of knowledge workforce management, referred to as the study of KWA, is happening.

Having been attracted by the promising benefits of KWA in PLC environments and having foreseen significant needs towards improving KWA practices, research of the abovementioned frontier is motivated. Distinguished from the previous work, this thesis will develop an effective approach to cultivating and optimizing KWA for overcoming the difficulties of knowledge workforce planning in semiconductor manufacturing, a representative PLC environment. The sections which follow describe detailed relevant background on the PLC, KWA and a RO solution approach.

1.2 Challenges Posed by The PLC Phenomenon

Semiconductor manufacturing is a representative high-tech industry that produces microelectronic devices, such as memory chips, micro components, and logic devices, wherein the PLC phenomenon is commonly observed. Their products are important inputs for the computer industry, consumer electronics, and communication equipment. About 30% of semiconductor products are memory chips, including DRAM, SRAM, ROM, EPROM, EEPROM and flash memories. The volatile memory chips, DRAM and SRAM, account for 90% memory chips in the market. Generations of semiconductor products are characterized by clear PLCs, during which unanticipated demand changes and production technology advances happen frequently, and the sales price drops rapidly. For example, DRAMs are classified as successive generations according to the storage capacity (e.g., 64k, 256k, and 1Mb), as illustrated in Figure 1.2. The PLC is referred to

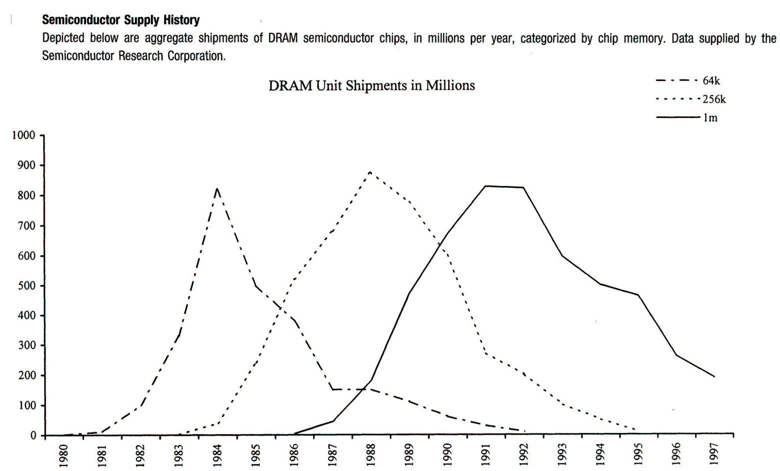


Fig. 1.2. PLCs of DRAMs (cited from Bollen (1999) in Management Science)

as the time horizon during which a generation of product exists in the market. PLCs of DRAM have been reported to be short, around 10 years [e.g., Bollen (1999), and Siebert (2003)]. Semiconductor manufacturing thereby bears great pressures to maintain a workforce that carries the right skills and timely knowledge. Robert Jones, an executive director of the National Alliance of Business said, "the quality of a company's workforce is its most important competitive advantage, . . . in manufacturing computer chips, 98% is ideas, skills, and knowledge and the rest is sand. Microsoft and IBM are more akin to championship sports teams where the quality of the human factor is essentially the only important variable to success".

Most of the knowledge workforce in semiconductor manufacturing work in a process called wafter fabrication, as Figure 1.3 illustrates. In wafer fabrication, the inte-

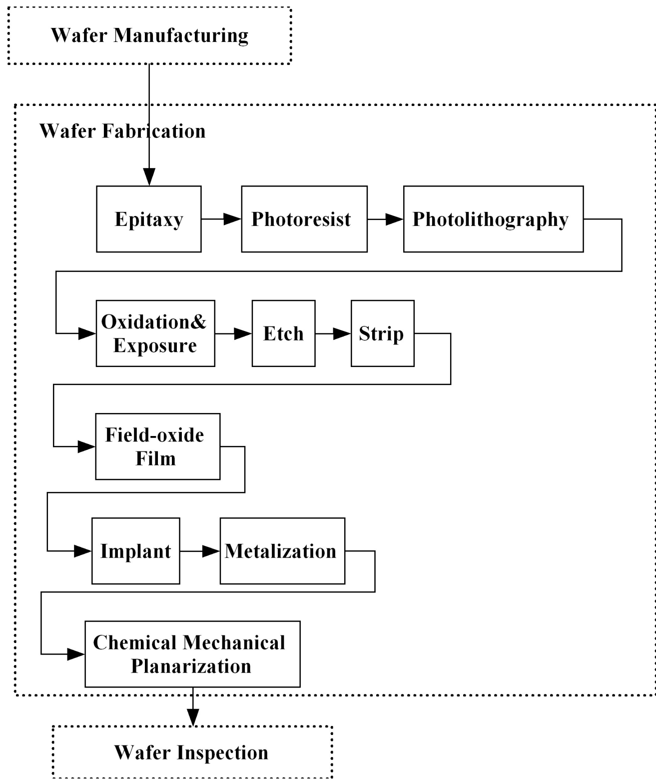


Fig. 1.3. Wafer Fabrication

grated circuit (IC or die) or a set of electronic components is produced by being fabricated on semiconductor material (e.g., silicon). The fabrication process involves building many layers of material, either conducting or insulating, on wafers. For example, DRAM chips are produced via etching circuitry on wafers of silicon. The complex process should be controlled precisely with respect to production environments (e.g., temperature, dust, and humidity), vibration, and facility settings. To maintain a stably high production quality thus is not easy. The PLC phenomenon severely intensifies the difficulty in that the rapid and unanticipated demand changes and production technology advances are very likely to cause many problems in wafer fabrication. Solving these problems to improve production quality is the major role of the knowledge workforce in semiconductor manufacturing. Thus, KWA should be a potential solution of pursuing the desired production quality through providing a proper capacity of problem solving in the PLC environment.

1.3 Viewing Knowledge Workforce Agility Through Real Options

An *option* is a contract to *buy* (i.e., *long*) or *sell* (i.e., *short*) a specific financial product referred to as the underlying instrument or underlying interest of the option (e.g., stock, exchange-traded fund, or similar product). The contract sets a specific price, called the *strike price* (or *exercise price*), at which the contract may be exercised. An option has an *expiration date*. When an option expires, it no longer has value. Options are classified into two categories, *calls* and *puts*, and either type can be bought or sold. People on different sides of the contract act in different manners. Call options give the option holder the right to buy the underlying instrument at the strike price at or before the expiration date, and put options give the holder the right to sell. Correspondingly, the writer of call (or put) options has the obligation to sell (or buy) the underlying instrument at the exercise price if the holder determines to exercise. When an option is bought (or sold), the money paid (or received) for the option is called the *premium*. The premium keeps changing over time. The value of an option contract is together determined by the price of underlying instrument and the exercise price. It is *in-the-money* if the value is positive, or else it is *out-of-the-money*. That is, a call (or put) option is in-the-money if the current market price of the underlying instrument is above (or below) the exercise price of the option, and out-of-the-money if it is below (or above) the exercise price. Options are categorized as *European options* and *American options* according to their expiration date. European options can only be exercised on the expiration date, whereas American options can be exercised on or before the expiration date. These basic concepts have been discussed in detail in the option literature [e.g., Hull (2003)].

The Black & Scholes (1973) and Merton (1973) option pricing research initiated an influential development of financial practices. Option valuation methods, numerical techniques, and applications have been surveyed comprehensively by Broadie & Detemple (2004). The influence of option pricing theory goes far beyond financial options, and real options (**RO**) remain a developing family of methods for applying the underlying conceptual framework of option pricing theory to real assets (i.e., non-financial instruments) [Merton (1998)]. The area of RO research has witnessed an important period when theories in finance are penetrating into many other areas, for example, operations research/management. RO exhibit an attractive fit in solving a range of risk-related problems arising from this period, and the research in this thesis employs this approach.

RO is particularly relevant to KWA in the sense that they share several similarities described below.

- **KWA in uncertain environments is an analogue to capacity options upon underlying stochastic processes**. Capacity options are a type of RO which allow the option holder to change the capacity in response to one or some underlying stochastic processes. The option holder gain certain amount of profits through manipulating the capacity options. Similar to capacity options, KWA endows knowledge workforce management a competency towards pursuing interest in highly uncertain environments. Management would earn extra profits with the facilitation of KWA.

- **Knowledge workforce represents knowledge capacity or a human asset**, which is created through capitalizing the workforce with required skills and knowledge. Thus, the creation of KWA is like a sequential investment on options in knowledge capacity under uncertainty. RO has been used to manage investments on physical capacity in high-tech industries [e.g., Benavides et al. (1999), Johnson & Billington (2003), and Wu et al. (2005)], so to generate KWA using RO can be an extension to knowledge capacity.

- **KWA is a special type of organizational capability**, which makes an organization respond to market and technology changes effectively. This capability could not be bought in the market or obtained by simple imitation. It can only be cultivated by the organization itself. RO has been suggested to be an appropriate methodology for managing the investment on this type of organizational capability [e.g., Kogut & Kulatilaka (1994)].

This thesis will model KWA as RO because RO properly capture the characteristic of KWA, and the *real options valuation* can optimize KWA and maximize the expected reward from it. KWA attained through the adoption of RO models and the implement of RO valuation methods is termed RO-based KWA in this thesis. There are two prerequisites for obtaining RO-based KWA in a PLC environment: first a mechanism of driving KWA is available, and second the PLC environment can be modeled as one or more underlying stochastic processes such as Brownian motion processes, mean reverting processes, Poisson jumping processes, or combinations of these.

1.4 Overview of Thesis

The PLC phenomenon is found to have placed significant pressures on high-tech industries which rely heavily on the knowledge workforce in transferring cutting-edge technologies into products. This is because market changes and production technology advances during the PLC cause great difficulties in predicting an appropriate demand on the knowledge workforce and in maintaining reliable performance. KWA exhibits an advantage of enhancing the capability of high-tech industries in operating the business in PLC environments. However, previous research on KWA is limited. A deep gap exists between the KWA concept and practices. This thesis is motivated to make efforts to fill the gap and to attempt to realize the benefits of KWA. RO is identified as an appropriate prototypical model of KWA in the sense that RO capture the characteristic of KWA − options in manipulating knowledge capacity, a human asset, or a self-cultivated organizational capability for pursuing interests associated with change.

This thesis will present an approach toward exploiting KWA in a representative PLC environment, semiconductor manufacturing, using RO. The major elements of this thesis are described below.

1. **Descriptive models of the PLC phenomenon**. The models should best capture the realism of the PLC phenomenon observed in semiconductor manufacturing, so that they make the cultivation/optimization of KWA better informed.

2. **The formulation of an agility-driven mechanism**. It should mathematically represent how an agility-driven mechanism creates capacity options in a knowledge workforce.

3. **The model of the knowledge workforce in wafer fabrication**. The model measures the role of the knowledge workforce and costs in attaining KWA, quantifying the elements of KWA that impact production.

4. **The optimization of KWA**. Algorithms and numerical methods for attaining the RO-based agility should be capable of solving the formulized problem which may be complex.

The feasibility of using RO to cultivate KWA will be justified after finishing the first two tasks, and the accomplishment of it will be finally conveyed by the other two tasks.

The thesis is organized into five Chapters followed by Appendices and a Bibliography. Chapter 2 reviews related work that either has an impact on the work of this thesis or informs this thesis directions of development. Chapter 3 presents the research framework for attaining RO-based agility, wherein the major bodies of work are developed. Chapter 4 assesses the significance of this work through mathematical justifications, study designs and detailed results analyses. Chapter 5 concludes this thesis and gives some thoughts on future research directions.

The fulfillment of the work is expected to provide an executable optimal solution for planning knowledge workforce in PLC environments, and to best bring out the profit growth from KWA. Implementing KWA via this approach has the potential to provide useful technology for high-tech industries. KWA may ameliorate the anxiety from rapid, large and unexpected changes, and may effectively turn such changes into attainable opportunities.

Chapter 2

Previous Work

This thesis benefits greatly from the research of others, which uncovered weaknesses to avoid, strengths to inherit, and directions to develop. The research stated in Chapter 1 related, either directly or indirectly, to research fields, such as workforce agility, real options (**RO**), product life cycle (**PLC**) phenomenon, and learning. This chapter reviews some of this related research to provide insight for the thesis. Not surprisingly, as the review process moves forward in this chapter, ideals in seemingly disparate fields combine to form an enlightening approach to exploiting knowledge workforce agility (**KWA**).

2.1 Workforce Agility

2.1.1 Agility Concept

The concept of agility originates from the report entitled *21st Century Manufacturing Enterprise Strategy* published by Iacocca Institute at Lehigh University in 1991. An agility forum based there has led to a successive agility studies, research programs, and national conferences. Despite of increasing interests in agility, the definition of this concept is sometimes vague in the associated research. For example, Dove (1994) defined agility as "change proficiency."Kidd (1994, 1995) felt that agility was a "reconfiguration capability,"rapidly responding to opportunities embedded in the changing market environment. Youssef (1994) took agility as "extraordinary capabilities to meet the rapidly changing needs of the marketplace"through "shifting quickly among product models or between production lines, ideally in real-time response. . . . "Goldman et al. (1995) stated that agility was "dynamic, context specific, aggressively change embracing, and growth oriented,"and is about "succeeding and winning profits . . . in the very center of competitive storms that many companies now fear."Nelson & Harvey (1995) identified agility as an "organization's capacity to respond rapidly and effectively to unanticipated opportunities and to proactively develop solutions for potential needs."Gunasekaran (1998) emphasized that agility was an "ability to thrive and prosper in a competitive environment of continuous and unanticipated change, to respond quickly to rapidly changing markets driven by customer-based valuing of products and services."Yusuf et al. (1999) anticipated agility to be a "successful exploration of competitive bases . . . "through "the integration of reconfigurable resources and best practices in a knowledge-rich environment"to "provide customer-driven products and services in a fast changing market environment."Katayama & Bennett (1999) felt that agility was a competitive strategy for "coping with demand volatility by allowing changes to be made in an economically viable and timely manner."Along the way of exploring the agility concept, researchers are gradually becoming convinced that making enterprises agile is the gateway towards successful survival in the 21st century.

Workforce agility is the human facet in the agility framework [see Gunasekaran (1998, 1999)]. As indicated in this agility study, the essence of workforce agility is the change proficiency in workforce capacity and capability, and training workforces to master timely knowledge and skills is a way of cultivating workforce agility. For example, Weick (1979) suggested that future workforce skills should be frequently anticipated by continuously examining environment dynamics. Prahalad & Hamel (1990) felt that capitalizing on employees' skills just ahead of requests was a means for creating agile workforces. Kidd (1994) emphasized the necessity of skilled, cooperative and motivated people for creating an agile manufacturing enterprise. Yusuf et al. (1999) thought that workforce were competent carriers on which an organization ultimately depended to infuse collective knowledge into products.

Breu et al. (2001) identified workforce agility as an important research topic which barely receives sufficient attention in previous agility studies. They emphasized that a role of employees in agile organizations, knowledge carriers, was ignored by previous agility studies. The work indicated that the knowledge workforce was the real element that workforce agility concerns, and workforce agility is indispensable in knowledge intensive industries.

2.1.2 Research Perspectives on Workforce Agility

The study of workforce agility has been examined from several angles in related research. Investigation from the perspective of human factors was initiated from a session entitled *Human Factors in Agile Manufacturing*, which was held at the 1995 Human Factors and Ergonomics Society Meeting in San Diego, CA. Plonka (1997), at that conference, reported the functions of an agile workforce as coping with uncertainty and responding to unexpected events. He claimed that incorporating human factors in the study of workforce agility is important because human factors can comprehensively support a continuous development and training process with professional theories, experiences, and practices. Further, he discussed potential agility-driven mechanisms for knowledge workforce, such as worker selection, acquisition of new knowledge, accelerated learning, and just-in-time delivery of training.

A representative study of workforce agility from the view of management is the research by Sumukadas & Sawhney (2004), in which a theoretical, hierarchical model was developed to interpret how workforce management practices (e.g., employee involvement, training and employee motivation) contribute to the generation of workforce agility. Two necessary components of a workforce agility framework were identified in this work. First, the ability of employees to be agile was a function of skills or structure elements of systems, which were obtained by training, job rotation, job enrichment, or teamwork. Second, the willingness of employees to be agile could be stimulated by appropriate rewards. The idea of using managerial practices to foster workforce agility shows that the overlap between management and human factors is an active place for conducting the study of workforce agility. Besides, they argued that workforce agility was not the performance of workers. The intrinsic characteristic of workforce agility is its potential impact on system performance, which suggests an idea of evaluating system profitability, brought by workforce agility, rather than workforce agility.

Hopp & Van Oyen (2004) studied workforce agility from the view of cross training and the coordination of cross trained workforces. They believed that cross training contributed to generating workforce agility since a cross-trained workforce represented a flexible capacity. They developed a strategic framework of workforce agility, in which four objectives (i.e., cost, time, quality, and variety) were identified. They additionally proposed a tactical framework including cross training skill pattern, worker coordination and team structure. Further, they classified major worker coordination policies into five categories: (1) scheduled rotation developed by mathematical programming approaches and used for balancing lines, managing bottlenecks, and releasing ergonomical stresses; (2) floating workers for production systems where "specialists are augmented by a smaller number of generalists who dynamically float to the operation at which they are needed;" (3) zoned worksharing for dealing with processing time variability; (4) worker-prioritized worksharing for allocating workers of a team to tasks in real time based on a prioritization of workers; and (5) craft approach. These researchers identified some research gaps and open problems, and thus they suggested several directions for future work. First, they felt that human behavior, which had been greatly ignored in previous research, should be considered. Second, previous work was mainly a study on the operational level, and it dealt with uncertainty on relative small scales. They suggested that future research should get insight into more uncertain environments and should develop more dynamic policies. Lastly, they identified the necessity of developing a micro-economic framework with costs incorporated for addressing workforce agility strategy and tactics. As a valuable work comprehensively summarizing the literature of workforce flexibility, it also identifies the insufficiency in the study of workforce agility.

Traditional cross training decisions have been challenged by Nembhard et al. (2002a) and Nembhard et al. (2005a) who questioned the reliability of the optimality of traditional workforce flexibility policies in a highly uncertain environment. They realized that, when the business environment changed, an optimal cross training decision might become suboptimal and a suboptimal decision possibly becomes optimal. They thus proposed to model workforce flexibility as flexible options and to formulate the cross training decision as an optimal stopping time problem. The work showed that, in a context where the product profit changed like an exponential Brownian motion process, a profit increment referred to as RO value was created through strategically cross training. Their work was a valuable attempt to utilize cross training, which was commonly used for mitigating production related risks through cultivating workforce flexibility, as a new tool for shielding manufacturers from market risks. More importantly, the work was a usefyk prototype study of workforce agility in the sense that it identifies a frontier whereon traditional solutions of workforce flexibility are no longer consistently effective, and introduces a method-family named RO for exploring the frontier.

2.2 Real Options

2.2.1 A Brief Overview of Option Pricing

Options is a type of *derivatives*. A derivative is "a financial instrument whose value depends on (or derives from) the value of other, more basic underlying variables"[Hull (2003)]. The underlying variable can be a traded asset (e.g., a stock), an index portfolio, a futures' price, a currency, or some measurable state variable (e.g., the temperature at some location) [Broadie & Detemple (2004)]. Options are distinguished from other derivatives, such as futures and forwards, in the sense that an option holder has a right rather than an obligation in tradings. Options are broadly traded for purposes of hedging risks, speculating future directions, or gaining some other financial benefits.

Black & Scholes (1973) developed a mathematical model for pricing options and managing risks. Merton (1973) provided an alternative proof for option pricing and generalizes the pricing framework. Their work substantially pushes the development of finance practices. "Paradoxically,"the mathematical model was developed, in theory, without referring to any empirical option pricing data. Traders in the Chicago Board Options Exchange (CBOE) begun, in 1997, to use Black-Scholes-Mertion model to speculate price and hedge risks in trading options. Publications and practices of option pricing grow fast, witnessing an evolution both in academia and in the derivative market. Merton and Scholes, thus, were awarded the 1997 Nobel Price in Economics for the "Black-Scholes-Merton option pricing"theory and the related work (Black was ineligible although he passed away in 1995). Meanwhile, they reviewed the past, examined the current progress, and gave insight into the future of options pricing [Merton (1998), and Scholes (1998)]. The journal of Management Science published, in 2004, an 50th anniversary article about option pricing, in which Broadie & Detemple (2004) comprehensively reviewed the option pricing literature, valuation models and applications till then, and they further identified the latest directions for development.

2.2.2 From Financial Options to Real Options

The RO valuation is an extension of the option pricing theory to options on real (i.e., non-financial) assets. However, the path from financial options to RO is not straightforward. People, competent at trading options in the derivative market, may not know how to identify and value RO [Amram & Kulatilaka (1999)]. Compared to financial options, which are usually well-posed questions, RO involves real-world complicated applications. Great efforts are needed to identify the options, develop models, and probe solutions, and this is why Amram & Kulatilaka (1999) emphasized that RO was "a way of thinking."

Some researchers have identified difficulties in using RO when they establish the path from financial options to RO. Although classic RO models and real-world applications have been broadly reported [e.g., Dixit & Pindyck (1994), and Schwartz & Trigeorgis (2001)], Lander & Pinches (1998) still identified three major difficulties in modeling and pricing investment opportunities using RO. First, existing RO models are not well understood by practitioners. Second, some necessary modeling assumptions may be violated in practice. Third, some mathematical issues limit the scope of applications. Bowman & Moskowitz (2001) examined a case of strategic decision making using RO, on which they conclude that the RO approach is still just a "theoretically attractive way to think about flexibility inherit in many investment proposals."Thus, seeking alternative modeling methods and valuation frameworks, which are more ready for implementation, to increase the width and depth of RO applications, is imperative.

Many researchers have contributed effort to introducing RO in a variety of engineering areas through probing innovative RO applications. For example, to address the need of organizations to measure the value of flexibility, Nembhard et al. (2000) proposes using an RO framework for managing production system changes. This framework was developed to use RO to evaluate the decision to use quality control charts [Nembhard et al. (2002b)], to pursue product outsourcing [Nembhard et al. (2003)], to evaluate supply chain decisions [Nembhard et al. (2005c)], and to model strategies aimed at reducing the environmental impact for a manufactured product [Nembhard et al. (2005b)].

A comprehensive overview of RO modeling and valuation by real-world users was provided by Miller & Park (2002) who felt that RO are in the early stage of development where many components of financial option pricing are utilized. They emphasized that, although financial options were a good foundation for RO, they should not limit the promising future of RO. Thus, they suggested to base RO on the foundation of financial options, properly combine RO with other useful tools and approaches as needed, and ultimately make RO "its own unique framework of addressing decision-making in a world of uncertainty."

2.2.3 Real Options versus Discounted Cash Flow

Traditional *discounted cash flow* (**DCF**) techniques were broadly used to evaluate projects. DCF techniques are based on the assumption of being certain about project cash flows, which is not true when decisions are made under uncertainty [e.g., Kulatilaka & Marcus (1992)]. The RO approach has the potential to solve the problem properly. Thus, uncertainty is nothing decision makers should fear or to avoid, and they can take advantages of it.

The trend that RO will be adopted broadly is manifested by how RO overcome limitations of the traditional DCF approach. First, in the traditional DCF approach, the *net present value* (**NPV**) of a project is calculated from a stream of expected net cash flows at a "risk-adjusted"discount rate which reflects the risks for the cash flows [e.g., Bernhard (1984), and Park & Sharp-Bette (1990)]. However, to properly estimate an appropriate risk-adjusted discounting rate is difficult [e.g., Fama & French (1997), and Miller & Park (2002)]. In the RO approach, *risk neutral valuation* (see Cox & Ross

(1976)) is used as opposed to DCF to strategically evaluate decision flexibility under uncertainty. Risk neutral valuation discounts future values using a *risk free rate*, which is attained via a probability transformation from the actual probability of underlying variable distribution to *risk-neutral probability* using Girsannov Theorem [Neftci (2000)]. As a result, utility of risk preference is not needed in the RO approach. Second, the traditional DCF techniques, nevertheless, ignore the flexibility to delay decisions or modify decisions when new information, opportunities, or threats come along the value chain. The probability distribution of NPV would be reasonably symmetric in the absence of a dynamic investment policy. The RO approach fully exploits advantages of flexibility in decision making, and thus, it leads to an asymmetry in the NPV distribution. Thus, the RO approach expands the value of investment opportunity by improving its upside potential, while limiting downside losses relative to manager's initial expectations under a deterministic investment policy [e.g., Kulatilaka (1988), Aggarwal (1991), Ernst & Kamrad (1995), Kulatilaka & Trigeorgis (1994), Panayi & Trigeorgis (1998), and Kulatilaka & Perotti (1998)]. Third, in the traditional DCF approach, high volatility represents high risks and high losses, which is indicated by a high discounted rate. In the RO approach, however, high volatility represents high values of opportunity. So RO hold a very different attitude towards uncertainty [Miller & Park (2002)]. Lastly, time compounds the effect of the risk-adjusted rate in traditional DCF techniques. However, RO evaluate long-term projects as more valuable based on the Black-Scholes model. RO overcome many limitations of traditional DCF techniques, and thus they are gradually adopted in many areas [Trigeorgis (1993), and Lander & Pinches (1998)].

Miller & Park (2002) emphasize that DCF and RO are complementary decision-making techniques. Despite the insufficiency of traditional DCF techniques, it is still a necessary part of RO in some circumstances because some inputs of RO are provided by DCF.

2.2.4 Capacity Planning Using Real Options

RO have been used to support capacity related decisions in highly uncertain environments, either on a strategic level or on an operational level. McDonald & Siegel (1985) showed that, when demand follows a Wiener process, a plant has the option to shut down if production does not generate enough profits. Pindyck (1988) models capacity expansion as RO for dealing with the irreversibility in capital investments, the uncertainty in returns, and the opportunity costs in capacity planning. Majd & Pindyck (1989) suggested properly utilizing operation flexibility, such as shutting down and later restarting, to master production capacity in dynamic economic environments. Abel et al. (1996) modeled choices in capacity expansion as call options and choices in capacity extraction as put options. Dangl (1999) used the RO valuation to determine the optimal timing of capacity investment and the optimal maximum capacity. His work showed that uncertainty substantially increases investments in capacity and delays the time to invest, even when uncertainty in demand is less substantial. Birge (2000) identified benefits of adjustable capacity and applied results of the options pricing theory to production planning. He incorporates risks in a planning model and correspondingly adjusts capacity and resource levels. Not all implementations of RO in capacity planning can be enumerated here, and comprehensive discussions on capacity planning using RO were provided by Trigeorgis (1996), Amram & Kulatilaka (1999), Schwartz & Trigeorgis (2001) and many other researchers.

A growing trend has been observed that RO are used to determine the optimal timing and scaling of capacity adjustments in high-tech companies [Johnson & Billington (2003)]. Wu et al. (2005) anticipate the RO approach to be a promising method for planning capacity in high-tech industries, which are characterized by large cash exposures, demand volatility, and changes in technology. They said that "each unit of capacity provides the firm options to produce a certain quantity of the product through its life cycle; and such options are referred to as the operating options. The investment in capacity is the premium for the option, in which the production cost corresponds to the exercise price."For example, Benavides et al. (1999) assumed that demand moved stochastically over time, just like a Geometric Brownian Motion process. Based on that assumption, they studied the optimization of capacity expansion in terms of timing, scale, and type for IC manufacturing. The work indicated that to split the investment on capacity into sequential small projects is more economical under conditions of uncertainty. However, some difficulties appear when applying classic option pricing models and results to capacity planning in semiconductor manufacturing. For example, Bollen (1999) noted that the standard Geometric Brownian Motion process is not appropriate for modeling the stochastic demand for DRAM products because they are characterized by historically short product life cycles and a well-defined bell-shaped pattern. Thus, he proposed a stochastic demand model containing two Geometric Brownian Motion processes, one with a positive drift rate connected to the other with a negative drift rate by a stochastic switch. His study indicated that a better understand of the business and production environment of semiconductor manufacturing was needed in order to properly apply RO to semiconductor manufacturing.

2.3 The PLC Phenomenon in Semiconductor Manufacturing

2.3.1 Market Environment Change

Demand straightforwardly manifests the characteristic of PLC phenomenon, and it has been broadly studied for several decades. Social scientists have interpreted it as a diffusion process, whereby a new product penetrates consumer categories that have different behaviors and adoption timing [e.g., Rogers (1962), and Katz et al. (1963)]. Polli & Cook (1969) described the PLC as a time-dependent sales model which was rationally supported by diffusion theory (Rogers (1962)) and was useful for marketing planning. Diffusion theory motivated the model developed by Bass (1969), in which the PLC was specified by the timing of adopting a new product and had a bell-shaped pattern for demand or sales (and an S-shaped pattern in cumulative demand or sales). This model was supported by historical data and its performance in forecasting [Bass (2004)]. Bass (1995) additionally investigated reasons why sales have a bell-shaped pattern over the course of the PLC by examining general attributes of marketing (e.g., price). This study has some similarities with the work by Levitt (1965) who comprehensively described the PLC phenomenon and analyzes the forces acting on it. Economists have concentrated more on demonstrating the existence of the bell-shaped pattern using traditional economic theories. For example, Russel (1980) noted a clear overlap between marketing and economics when he replicated the bell-shaped pattern. He argued that the timing of adoption was determined by consumer heterogeneity. If income manifests individual heterogeneity, an approximately log-normal density function of population across their incomes should exist, which is commonly seen in practice [e.g., Aitchison & Brown (1969)].

Demand during the PLC seldom exhibits a smooth bell shape. It is actually volatile beyond the pattern and even substantially deviates from it. Rosegger (1986) emphasized that variations beyond the bell-shaped pattern were at least as important as the pattern itself, and yet they might not be properly explained by diffusion theory. Bass (2004) also felt that problems related to the stochastic PLC deserve additional attention. Bollen (1999) developed an RO model for the PLC phenomenon. His work suggested a way of incorporating the uncertainty of the PLC environment in decisions.

Existing models of underlying processes seemingly provide candidates for modeling the PLC phenomenon, such as Geometric Brownian Motion (**GBM**) processes, Poisson jump processes, mean-reverting processes, and combinations of these [Hull (2003)]. However, these models can not be applied directly. For example, Bollen (1999) showed that a single GBM process with a constant positive drift rate was not a complete model for demand during the PLC. Thus, he proposed a model containing two GBM processes, one for the growth phase, and one for the decay phase connected with a stochastic switch. The Bollen model captures the trend of demand movement and the uncertainty of it during the PLC, so it can provide improved results over the previous research. However, the Bollen model may have two obvious limitations. First, it ignores the fact that the speed whereby a new product penetrates the market may actually be related to the market size, the initial adoption level, and the length of PLC. These relations are properly built in the Bass (1969) model which is based on diffusion theory. Thus, the first limitation possibly be remedied through adoption of the well-developed relations in the Bass model. Moreover, incorporation of these two models empowers the Bass model as well, because the volatility observed on the demand side could not be fully explained by diffusion theory [Rosegger (1986)]. The second limitation of the Bollen model arises from the manner in which it handles model uncertainty. For example, the length of the PLC is unknown early in the PLC, so the belief about the length of the PLC is in a form of probability. When moving along the PLC, more accurate information about the length of the PLC should become available. However, the Bollen model never utilizes this possibility of imformation improvement during the PLC. An extension, based on the methods of Bass (1969) and Bollen (1999), would provides a more complete representation of demand during the PLC by inheriting some beneficial properties of each.

2.3.2 Production Environment Change

The second clear characteristic of the PLC phenomenon observed in semiconductor manufacturing is process changes associated with adoption of production technology advances. Process changes have been reported to interrupt learning, either on an individual level or on an organizational level. Hatch & Mowery (1998) studied the relationship between process changes and learning-by-doing in semiconductor manufacturing. Learning-by-doing, defined by them, was "deliberate activities for improving yields and reducing costs, rather than the incidental by-product of production volume."They found that process changes significantly disrupt ongoing learning activities in that they need engineering resources for solving problems arising in the new processes. Carrillo & Gaimon (2000) noted that process changes, which involved updating hardware/software and modifying process procedures, will ultimately increase effective capacity. Meanwhile, they also found that process changes lower short-term capacity since productivity decrease, equipment downtime, quality problems and any others were observed.

Process changes in high-tech industries were investigated in the work by Terwiesch & Xu (2004), wherein process changes and learning were taken as a conflict pair. They noted that high-tech industries were often forced to bring products to market before manufacturing processes were full understood because of short PLCs and the rapid price erosion. The gap between what processes are described in recipes and how the processes are actually operate should be filled. The process by which productivity or production quality increases is "learning"in this currence. However, in order to be competitive among peers, many high-tech companies must often refine process recipes, which is referred to as process changes. Sources of refinements are classified as internal and external technologies. The former includes R&D and process re-engineering, and the latter leads to introducing or updating equipment and software. If products are introduced to the market in a rush, process changes continue throughout the whole PLC, not at one time. The development of new knowledge and routines is crucial to making process changes succeed, and yet reduces the effective knowledge of the workforce (not because of forgetting but of partially losing its relevance). Thus, an dynamic optimization problem usually is formulized for determining the tradeoff between learning and process changes. The research on process changes and learning indicated that workforce knowledge (**WK**) exhibited clear dynamics in attempts to adopt production technology advances. Thus, management of a knowledge workforce in PLC environments should consider especially the impact of WK dynamics (or the unreliable performance of the knowledge workforce) on production.

2.4 Learning

Learning was first investigated in the airframe industry [e.g. White (1936), Asher (1956), Alchian (1963), and Hartley (1965)]. This concept has been adopted as a management tool or an operational measurement by many other industries [see Hatch & Mowery (1998)]. Learning, as a process of experience or knowledge accumulation, has a variety of forms in different industries, for example, cost or price reduction [e.g., White (1936), Hartley (1965), Spence (1981), Fudenberg & Tirole (1983), Lieberman (1984), and Argote et al. (1990)], productivity rise [e.g., Mazur & Hastie (1978), and Nembhard & Uzumeri (2000)], and quality improvement [e.g., Fine (1986), Tapiero (1987), Mukherjee et al. (1998), and Serel et al. (2003)].

Levy (1965) conducted a taxonomy study on learning. He suggested classifying learning into three categories: autonomous learning, planned or induced learning, and random or exogenous learning. Autonomous learning is the improvement due to on-the-job learning or training, whereas planned or induced learning is the result of a firm's managerial actions for increasing the productivity or reducing production cost. Random or exogenous learning is beyond the firm's control or expectation. Learning curves usually have three major proxy types. They are cumulative output [e.g., Spence (1981), Fudenberg & Tirole (1983), and Lieberman (1984)], cumulative investments [e.g., Arrow

(1962), Sheshinski (1967), and Rosen (1972)], and time [e.g., Cooper & Charnes (1954), Rapping (1965), David (1970), and Stobaugh & Townsend (1975)].

2.4.1 Learning in Semiconductor Manufacturing

Yield improvement is the predominant form of learning in semiconductor manufacturing. Siebert (2003) investigated learning-by-doing in a PLC environment and noted that the learning-by-doing effect is less important than expectation, and successive product evolutions might be the reason. Terwiesch & Xu (2004) reached a similar conclusion when they studied learning and the opposite, process changes, during production ramp-up. They showed that yield droped substantially when production scale ramped up. Weber (2004) felt that learning effectively raised the production profit because yield improvement was a process that engineering, technicians and managers engage to reduce faults. These representative studies have demonstrated that creation and management of problem-solving capacity is the essence of mastering yield and production revenues.

Differences between learning via problem-solving and learning-by-doing have been reported by scholars from different perspective. Mody (1989) viewed learning as a continuous process of knowledge creation by teams of skilled engineers who are sent to shop floors for trouble shooting. He showed that learning was a managerial practice for improving production profits through knowledge generation and transfers, rather than a mere by-product of production. Adler & Clark (1991) explicitly differentiated learning via managerial actions from learning-by-doing by defining first-order and second-order learning. Dorroh et al. (1994) took knowledge as a production input, not a by-product of experience. They thereby differentiated investments in knowledge acquisition from the learning-by-doing, and further showed that the investments were costly. However, the investments have long-term profits, since they will be paid off when the increased learning rate meets future opportunities.

The problem-solving capacity, as an important driver for yield improvement, is crucial to knowledge-intensive industries. Iansiti (1995) identified that the problem-solving behavior of individuals drived the generation of new knowledge for new product development. Gaimon (1997) found that the volume of a knowledge workforce and the skill levels of the individuals in the workforce affect the output increment. So, he quantifies the relationship between output and the knowledge workforce. Macher & Mowery (2003) recognized that detailed engineering analyses of yield problems and the implementation of corrections improved the performance of semiconductor manufacturing effectively.

Adjusting the problem-solving capacity is less straightforward than the physical capacity. Problem-solving capacity is cultivated via workforce managerial practices such as training, teaming or motivating. To provide an appropriate employee capacity for stochastic demand, Anderson (2001) developed an optimal staffing policy which involved training unproductive apprentices or laying off experienced employees. Bailey (1998) discussed how skills and knowledge were created as employees team up to address production problems at shop floors of fabrication. He studies three types of team structure in semiconductor manufacturing: continuous improvement teams (CITs), quality circles (QCs), and self-directed work teams (SDWTs). He found that CITs leaded to the highest direct or indirect productivity, however, the other two should not be dismissed.

Sattler & Sohoni (1999) studied participative management in semiconductor manufacturing. They argued the reason that semiconductor manufacturing was a industry where human resource management was important, and concluded that high level employees (i.e., engineers) could focus on major improvement projects rather than troubleshooting exercises if lower level employees (i.e. operators and technicians) became involved in problem solving and decision making. Similar results are reported by Appleyard & Brown (2001) who showed that well-functioning teams, consisting of continuously trained engineers and initially trained technicians, were crucial to achieving good performance in fabrication.

2.4.2 Viewing Actions for Improving Learning as Investments

Many researchers suggested viewing actions for improving learning as investments since they observed uncertainty in returns. For example, Dorroh et al. (1994) studied the balance between allocating resources to the production of output and to the production of knowledge. The former created an immediate revenue; whereas, the latter aimed at potential future profits. Fine & Porteus (1989) showed that investments in learning contributed to gaining strategic long-term profits. They suggested splitting the investment in learning as a sequence of small investment opportunities over the time horizon when returns from the investment were uncertain. Chand et al. (1996) showed that employees' efforts in identifying and solving problems on shop floors were a process of knowledge creation and production improvement. Costs are associated with such activities, because employees and equipment time that otherwise are used for producing an immediate revenue are used. The costs are possibly reduced by long-term benefits.

Similarly, Terwiesch & Bohn (2001) studied learning in high-tech industries where sales prices fall rapidly. They considered deliberate experiments as learning activities which occupied production capacities in the short term but had potential to create long-term values. They, thereby, accepted exploration of trade-off between generating instant revenues and improving learning as investments.

Some other scholars have treated the acquisition and retention of knowledge as investments because efforts spent in knowledge management would be beneficial in the future. For instance, Rosen (1972) claimed that knowledge is firm-specific, capital goods, an input, and an output of production. He believed that a view of investment is necessity because the remaining production revenue would be affected by the learning rate which was determined by current volume of output. Dutton & Thomas (1984) classified factors which leaded to process improvement into four categories, varying according to origin (exogenous and endogenous) and type (autonomous or induced). They stated that knowledge management behaviors of a company, such as investments in learning, influenced the rate of process improvement. Hatch & Mowery (1998) studied how to improve production yield through management of learning when new processes were introduced into semiconductor manufacturing. They showed that learning in the early stages of production was a function of engineering resources allocated to problem-solving activities. Therefore, the management of knowledge workforce in semiconductor manufacturing is capable of improving yield.

Chapter 3

A Framework for Attaining RO-Based KWA

The rationale for using real options (**RO**) based knowledge workforce agility (**KWA**) to release pressures that the product life cycle (**PLC**) phenomenon placed on high-tech industries was described in the previous two chapters. RO-based KWA is realized by accomplishing several tasks organized in a framework. This chapter presents the framework wherein RO-based KWA is attained through modeling KWA as capacity options in a knowledge workforce and optimizing KWA using the RO valuation. The optimization in the framework is informed by a model of the PLC phenomenon, is conveyed through a model of the knowledge workforce, and is fulfilled by well-designed optimization schemes. In order to make this chapter as focused as possible, basic background materials and relative mathematical derivations are presented in Appendices A-I.

3.1 Modeling Demand Changes

Market demand conveys important information about customers, competitors, the market, and even the manufacturer itself. However, the information is often reflected by demand uncertainty, which can be separated into two components, generally. One source of the uncertainty can be eliminated gradually through demand learning, with information disclosure as a result. The other source of uncertainty consists of unpredictable factors, for example, demand volatility, and so is irreducible.

This thesis is interested in developing a demand model with the following characteristics. (1)The model conveys quantitative information about the PLC phenomenon, representing demand either with a closed mathematical form or a concisely numerical layout. (2) The model inherits advantages of existing models and captures more realism than prior models, so it can be fitted by real data and be used to interpret observations. (3) The model has clear mathematical descriptions about both sources of uncertainty, and thus it is informative for exploiting the advantage of KWA.

3.1.1 Demand Model Formulation

Demand during the PLC is modeled as a GBM process, a common type of underlying process models in the RO literature [e.g., Pindyck (1988), Trigeorgis (1996), Benavides et al. (1999), Bollen (1999), and Broadie & Detemple (2004)]. The evolution of demand is addressed by the drift rate of the GBM process, and the stochasticity in demand is represented by a standard Wiener process (see page 176-177 in Neftci (2000)) on the trend. More specifically, if D_t is the demand at time t during the PLC [0, T] (T is the length of PLC, which is uncertain), the relative change in demand during the interval $[t, t + dt]$ is shown in Equation (3.1).

$$\frac{dD_t}{D_t} = \mu_t(M, D_0, T_m)dt + \sigma dW_t \tag{3.1}$$

In Equation (3.1), $\mu_t(M, D_0, T_m)$ (μ_t will be the simplified notion in the remains of this thesis) is the drift rate in demand. It varies over time and makes the expected demand exhibit a bell shape over the PLC. In addition, it is parameterized by M, the expected cumulative demand, D_0, the initial demand, and T_m, the time of demand maturity (it happens when the ascending trend of demand stops and switches to a descending trend). W_t is a Wiener process for modeling the unpredictability in demand. σ is the demand volatility, which measures the scale of unpredictability. σdW_t thus represents the unanticipated part of the relative change in demand during $[t, t+dt]$. Any change in W_t over the time interval dt, ΔW_t $(= W_{t+dt} - W_t)$, satisfies $\Delta W_t = \epsilon_t \sqrt{dt}$ ($\epsilon_t \sim N(0,1)$, and $E[\epsilon_t \epsilon_s] = 0$ for $t \neq s$). Thus, $\Delta W_t \sim N(0, dt)$ according to the Central Limit Theorem [see page 177 in Neftci (2000)]. As a result, the relative change in demand during time interval ΔT is normally distributed, as indicated in Equation (3.2).

$$\frac{D_{t+dt} - D_t}{D_t} \sim N\left(\int_t^{t+dt} \mu_s ds, \sigma^2 dt\right) \tag{3.2}$$

The variance of demand increases linearly over time in Equation (3.2), so an actual demand trajectory over the PLC may deviate significantly from a perfect bell-shaped pattern. Thus, Equation (3.2) better describes demand during the PLC than deterministic demand models.

3.1.2 The Bell-shaped Pattern of Demand over The PLC

The drift rate in demand, μ_t, specifies the trend rate of demand movement as well as how quickly a new product penetrates the market. It is important information in some RO problems wherein the traditional risk neutral valuation principle (Hull (2003)) does not work, and this thesis falls in this category. The tradition risk neutral valuation principle assumes that the underlying process is correlated to some traded asset in the market, so the risk free interest rate, r_f, can replace for the drift rate, μ_t. However, it is difficult to find any traded asset in the market to which the demand of a new product is correlated. A modified risk neutral valuation principle thus is adopted for dealing with this difficulty. Now r_f is only used in discounting expected future values, and μ_t is kept in the RO valuation except that it is adjusted by λ, the market price of risk, to become $\mu_t - \lambda\sigma$ [Hull (2003)].

For demand over the PLC to take on a bell-shaped pattern, μ_t is modeled as a linear decreasing function of time, as in Equation (3.3).

$$\mu_t = \frac{\beta(M, D_0, T_m)^2}{T_m} - \frac{\beta(M, D_0, T_m)^2}{T_m^2} t \tag{3.3}$$

Appendix B shows how Equation (3.3) is derived. $\beta(M, D_0, T_m)$ (β will be the simplified notation in the remains of this thesis) is the ratio of T_m to σ_{T_m} (T_m is uncertain, which is indicated by a probability distribution, and σ_{T_m} is the standard deviation of T_m). It describes the shape of the bell pattern, and it is a function of M, D_0 and T_m according to Equation (B.7).

The drift rates at different values of T_m are illustrated in Figure 3.1, along with the corresponding expected demand curves. Figure 3.1 shows that demand tends to rise/decay quickly if T_m is short, indicating that the speed whereby the product spreads in the market is related to the length of the PLC. In addtion, the figure tells us that the initial drift rate increases sharply when the PLC shrinks. So in one sense, the drift rate function is a mathematical representation of the notion that short PLCs may pose challenges to high-tech industries.

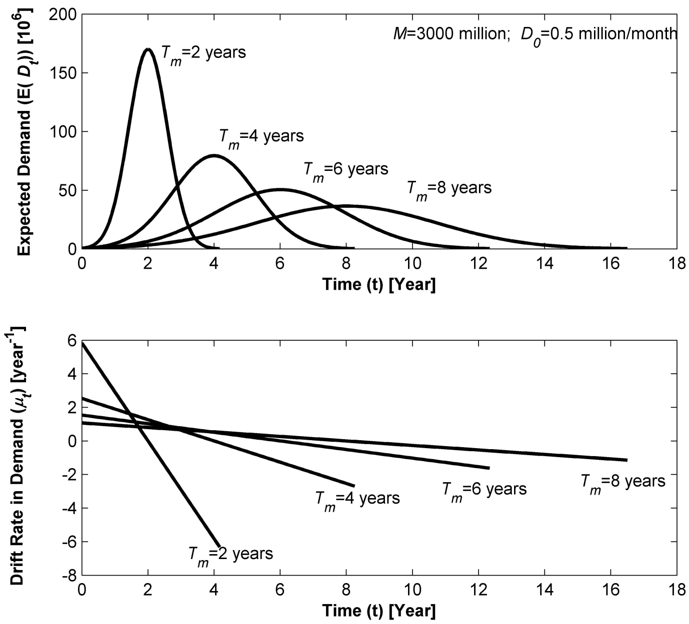


Fig. 3.1. Expected Demand and Drift Rate in Demand Over The PLC

Demand at time t is obtained by applying $It\hat{o}$'s lemma (See Appendix A) and integrating Equation (3.1), yielding the expression in Equation (3.4).

$$D_t = D_0 e^{\left(\frac{\beta^2}{T_m}\left(1-\frac{t}{2T_m}\right)-\frac{1}{2}\sigma^2\right)t+\sigma W_t} \tag{3.4}$$

Model parameters D_0, M, T_m and σ are needed for expressing demand in Equation (3.4). D_0 is the only directly observable parameter. M is similar to the concept of the total number of adopters in the Bass (1969) model, and the estimation of σ is well discussed in the RO literature [e.g., Hull (2003)]. M and σ of the previous generations of product can be obtained through fitting the demand model with history data, as Section 3.1.3 will demonstrate, and they are valuable references for the estimation of M and σ in the current generation. T_m, however, is unknown in the early PLC. Uncertain parameter T_m is the other source of demand uncertainty. The demand distribution is condition on T_m, indicating that the accuracy of the information about T_m impacts the knowledge of demand distribution. Bayesian estimation is an approach for learning T_m through observing demand continuously, as will be discussed in Section 3.1.4.

3.1.3 Demand Model Fitting and Verification

A sample of sales data during the PLC cited from Siebert (2003) is illustrated in Figure 3.2. Assuming that sales data is a reasonable representation of demand, the sample in Figure 3.2 can be used for demonstration of model fitting and verification.

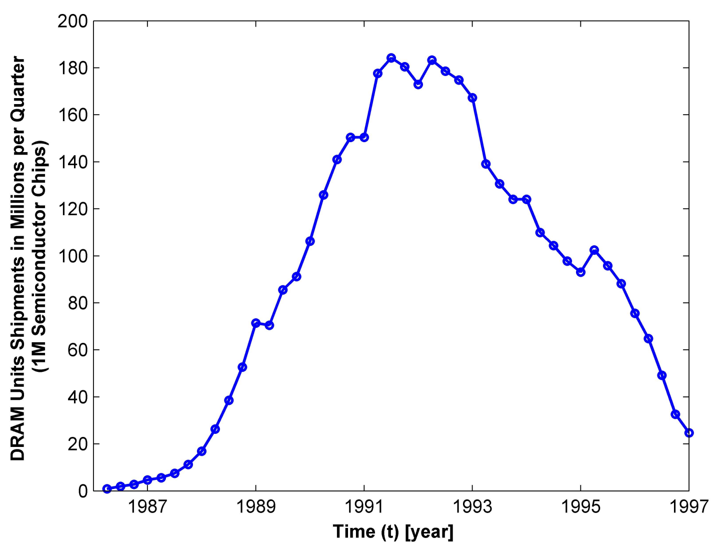


Fig. 3.2. A Sample Trajectory of Stochastic Demand Over The PLC

This sample path exhibits stochasticity over the PLC instead of having a smooth bell shape. It contains 44 records of quarterly demand (i.e., the time interval ΔT=0.25

years), denoted as D_i (i=0,1,...,43), so there are 43 observations of relative demand change, $\frac{D_i - D_{i-1}}{D_{i-1}}$ $(i = 1, \ldots, 43)$. The linear regression is applied to $\frac{D_i - D_{i-1}}{D_{i-1}\Delta_T}$ to examine the linearity of the drift rate function μ_t, to justify the Wiener process W_t, and to fit model parameters. Results of the regression analysis are listed in Appendix C. A regression function $\hat{\mu}_t = 1.68 - 0.26t$ is obtained. The P-value of regression is less than 0.0001, R^2 is equal to 0.75, and R^2_{adj} is 0.74, which suggest that the regression function is statistically significant and is properly fitted. Assumptions about the regression residual are no autocorrelation and of normal distribution $N(0, \frac{\sigma^2}{\Delta T})$. The Durbin-Watson statistic equals 1.51, and the P-value for first order autocorrelation is 0.235, which means with probability 23.5% we can reject the hull hypothesis of non autocorrelation. Although the P-value is greater than 0.05, in a real case this p-value is fine. If we choose a drift rate function which better describe the trend of demand change, the p-value will decreases. Thus, the null hypothesis of no autocorrelation can be treated as valid. The P-value of Anderson-Darling test is 0.172, so the normality assumption is proved to be fine. Therefore, the existence of Wiener process W_t on the bell-shaped pattern is justified.

The regression function provides the estimates of $\frac{\beta^2}{T_m}$ (the intercept of the regression function), $\frac{\beta^2}{T_m^2}$ (the slope of the regression function), and $\frac{\sigma^2}{\Delta T}$ (the mean squared error of regression), respectively. They are used in Equations (3.5)-(3.8) for estimation of the model parameters.

$$T_m = \frac{\beta^2 / T_m}{\beta^2 / T_m^2} \tag{3.5}$$

$$\beta = \sqrt{\frac{\beta^2}{T_m} \times T_m} \tag{3.6}$$

$$\sigma = \sqrt{\frac{\sigma^2}{\Delta_T} \times \Delta T} \tag{3.7}$$

$$M = \frac{D_0\sqrt{2\pi}T_m}{\beta e^{-0.5\beta^2}\Delta T} \tag{3.8}$$

σ, T_m and β are estimated to be 0.24, 6.43 years and 3.29, respectively. Based on the facts in regression, Equation (3.1) is justified as a reasonable model for the stochastic demand illustrated in Figure 3.2.

3.1.4 Bayesian Estimation of T_m

Equation (3.3) shows that the demand distribution relates to a non-predetermine parameter T_m, so the uncertainty in T_m intensifies the uncertainty in future demand. Bayesian estimation has a contribution of improving the knowledge about future demand through gaining more accurate information about T_m by learning demand.

Θ represents the uncountably infinite set containing all possible outcomes of T_m, and θ is a value of T_m. X denotes the countably finite set consisting of all possible values of D_t ($\forall t \in [0, T]$), and x is a possible observation of D_t. $f_{D_{t+dt}}(\tilde{x}|\theta, x)$ represents the distribution of future demand $D_{t+dt}(dt \geq 0)$, wherein $\tilde{x}$ is a possible value of future demand. Equation (3.9) shows that $f_{D_{t+dt}}$ conditions on θ, the estimate of T_m, and x, the observation of D_t.

$$f_{D_{t+dt}}(\tilde{x}|\theta, x) = \frac{1}{\sqrt{2\pi dt}\sigma} e^{-\frac{\left(\frac{\tilde{x}-x}{x} - \left(\frac{\beta(M,D_0,\theta)^2}{\theta} - \frac{\beta(M,D_0,\theta)^2}{\theta^2}\left(t+\frac{dt}{2}\right) - \frac{\sigma^2}{2}\right)dt\right)^2}{2dt\sigma^2}} \tag{3.9}$$

$$\theta \in \Theta, \quad x \in X, \quad \forall \tilde{x} \in X$$

The belief about T_m usually is in the form of a probability distribution, indicating the uncertainty in T_m. Bayesian estimation makes the belief about T_m condition on x, the observation of the current demand D_t, indicated as $\phi_{T_m}(\theta|x)$. As Equation (3.10) shows [see Berger (1985)], Bayesian estimation will update $\phi_{T_m}(\theta|x)$ to $\phi_{T_m}(\theta|\tilde{x})$ in dt when $\tilde{x}$, the subsequent demand after x, is observed.

$$\phi_{T_m}(\theta|\tilde{x}) = \frac{f_{D_{t+dt}}(\tilde{x}|\theta, x)\phi_{T_m}(\theta|x)}{\int_{\theta\in\Theta} f_{D_{t+dt}}(\tilde{x}|\theta, x)\phi_{T_m}(\theta|x)d\theta} \qquad \tilde{x} \in X, \forall\theta \in \Theta \tag{3.10}$$

Right after the update is accomplished, $\tilde{x}$ in Equation (3.10) turns to x, and correspondingly, $\phi_{T_m}(\theta|\tilde{x})$ becomes $\phi_{T_m}(\theta|x)$.

An initial belief about T_m is usually provided before a product enters the market since some factors (e.g. the expected economic advantages in terms of "new") provide some information about how quickly the product will penetrate the market. The initial belief is in the form of a probability distribution, $\phi_{T_m}(\theta)(\theta \in \Theta)$. For example, Bollen (1999) estimates T_m as normal distributed, whose mean is μ_{T_m} and standard deviation is σ_{T_m} (i.e., N($\mu_{T_m}, \sigma^2_{T_m}$)). Therefore, $\phi_{T_m}(\theta|x)$ at the beginning of the PLC is independent of the initial demand, equivalent to $\phi_{T_m}(\theta)$.

Figure 3.3 illustrates how Bayesian estimation improves the knowledge about T_m. The top plot in Figure 3.3 displays the progress that the probability distribution of T_m is updated by Bayesian estimation. The initial belief about T_m is a normal distribution whose mean is five years with a standard deviation of one year. Bayesian estimation updates the belief about T_m over the course of PLC, and the distribution of T_m is narrowed and gradually stays around 3.77 years, the actual value of T_m. The bottom plot illustrates the estimation error during the process, which drops quickly. The observations in Figure 3.3 inform us that Bayesian estimation is an effective way of improving the knowledge about T_m and by extension, μ_t.

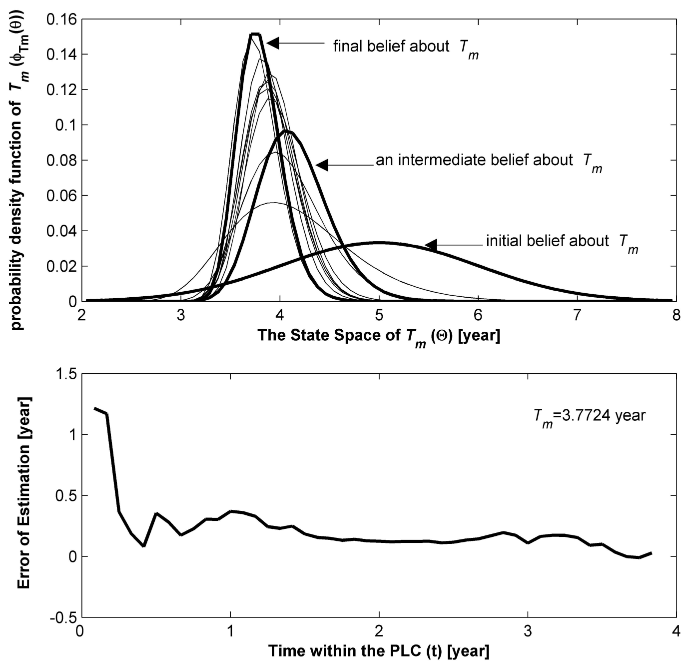


Fig. 3.3. Bayesian Estimation of T_m

3.2 Modeling WK Dynamics in Adoption of Technology Advances

Production processes have to be changed frequently to adapt to production technology advances during the PLC, either internal (e.g., internal research and development) or external (e.g., new technology created outside the firm) [e.g., Terwiesch & Xu (2004)]. Process changes interrupt learning, either individual or organizational, during the PLC. Workforce knoweldge (**WK**) thereby often lose partial relevance to what they attempt to fulfill, termed WK dynamics. Training workforce continuously is an approach to recover WK. The amount of time spent on continuous training is manifest of the level of WK. The less the relevant WK that the workforce have, the more the amount of time spent on continuous training. Thus, this thesis describes WK dynamics in adoption of production technology advances through modeling the change in training efforts during the PLC. More specifically, the percent of labor time spent on continuous training (**CTT**), η_t, is modeled to manifest how the knowledge workforce is influenced by the production environment change.

3.2.1 The CTT Model Formulation

Unexpected arrivals of technology advances are discrete and unancitipated, and a Poisson jump process is usually used to represent technology advances [e.g., Kortum (1997), Ahn & E. (1988), and Boston & Pointon (1999)]. The training effort rises sharply in adoption of technology advances, and thus η_t exhibits discrete upward jumps during the PLC. η_t descends gradually in a decreasing pace after jump due to the learning effect (i.e., WK increases during training, but at a reduced speed because opportunities of improvement are exhausted gradually. As a results, η_t is assumed to decrease in an exponential manner). η_t thus can be represented by a Poisson jump process plus a mean-reverting process , as indicated in Equation (3.11).

$$d\eta_t = \alpha_\eta \left(\eta_m - \eta_t\right) dt + \sigma_\eta dW_{\eta t} + r_\eta dN_t \tag{3.11}$$

α_η in Equation (3.11) is the reverting speed after jump, and it represents the learning capability of the knowledge workforce. N_t is a Poisson process with the jump intensity λ_η, and it accounts the number of unanticipated jumps of η_t up to t. r_η is the jump size which is assumed to be a constant in this thesis. σ_η is the volatility of the mean-reverting process, and $W_{\eta t}$ is a Wiener process. They together manifest the unpredictability in the mean-reverting process. η_m is the equilibrium level of η_t.

Equation (3.12) is the integral form of Equation (3.11), and Appendix (D) shows how it is derived.

$$\eta_t = e^{-\alpha_\eta t}\eta_0 + \left(1 - e^{-\alpha_\eta t}\right)\eta_m + \sigma_\eta \int_0^t e^{\alpha_\eta (s-t)} dW_{\eta s} + r_\eta \int_0^t e^{\alpha_\eta (s-t)} dN_s \tag{3.12}$$

η_0 in Equation (3.12) is the initial value of η_t.

Equations (3.13) and (3.14) are the expected value of η_t ($E[\cdot]$ denotes the operator of expected value) and the variance of it ($VAR[\cdot]$ represents the operator of variance), respectively. Appendix E shows how $E[\eta_t]$ and $VAR[\eta_t]$ are derived.

$$E[\eta_t] = e^{-\alpha_\eta t}\eta_0 + \left(1 - e^{-\alpha_\eta t}\right)\left(\eta_m + \frac{\lambda_\eta r_\eta}{\alpha_\eta}\right) \tag{3.13}$$

$$VAR[\eta_t] = \left(1 - e^{-2\alpha_\eta t}\right)\frac{\lambda_\eta r_\eta^2 + \sigma_\eta^2}{2\alpha_\eta} \tag{3.14}$$

The expected value and the variance of η_t, as in Equations (3.13) and (3.14), reveal the layout of η_t over the PLC. $E[\eta_t]$ starts at η_0 and goes to $\eta_m + \frac{\lambda_\eta r_\eta}{\alpha_\eta}$ asymptotically. $VAR[\eta_t]$ begins at zero, increases over time in a decreasing pace, and ceases at $\frac{\lambda_\eta r_\eta^2 + \sigma_\eta^2}{2\alpha_\eta}$ asymptotically.

3.2.2 Risk-Neutralized η_t

The Poisson process, N_t, has a positive trend $\lambda_\eta t$ over time, so η_t is not a Martingale process (i.e., a trendless stochastic process). A compensated Poisson process is defined by eliminating the trend $\lambda_\eta t$, as indicated in Equation (3.15) (See chapter 6 in Neftci (2000)).

$$N_t^* = N_t - \lambda_\eta t \tag{3.15}$$

The market price of jump risk is zero because the jump risk can be assumed to be diversified [Merton (1976)]. Thus, by replacing N_t with N_t^* in Equation (3.12), the risk-neutralized form of η_t is obtained, as in Equation (3.16).

$$\begin{aligned} \eta_t =& e^{-\alpha_\eta t}\eta_0 + \left(1 - e^{-\alpha_\eta t}\right)\left(\eta_m - \frac{\lambda_\eta r_\eta}{\alpha_\eta}\right) \\ &+ \sigma_\eta \int_0^t e^{\alpha_\eta (s-t)} dW_{\eta s} + r_\eta \int_0^t e^{\alpha_\eta (s-t)} dN_s \end{aligned} \tag{3.16}$$

The expected value of the risk-neutralized η_t is $e^{-\alpha_\eta t}\eta_0 + \left(1 - e^{-\alpha_\eta t}\right)\eta_m$, and the variance of the risk-neutralized η_t is $\left(1 - e^{-2\alpha_\eta t}\right)\frac{\lambda_\eta r_\eta^2 + \sigma_\eta^2}{2\alpha_\eta}$, correspondingly.

3.3 Formulation of Capacity Options in a Knowledge Workforce

Semiconductor manufacturing consists of three major phases: design and mask creation, front-end processing (wafer fabrication) and back-end processing (assembling and testing). The second phase is where the knowledge workforce contributes the most to production quality improvement in way of solving problems arising from this phase.

The PLC phenomenon causes an unstable and unpredictable demand on the knowledge workforce and unreliable performance, and KWA is modeled as capacity options in a knowledge workforce for addressing the difficulties posed by the PLC phenomenon. Accompanying successive generation replacements, the whole workforces flow gradually from old generations to new ones. The time window that more than two generations are simultaneously in production is less than one year. Although the overlap of two successive generations is longer than the overlap of three, the new generation, as the most competitive product in the market, has a higher priority than the old one. Thus, this thesis simplify the problem substantially by formulating a capacity planning decision for only one generation of product. Without further explanation, the "knowledge workforce", is referred to as the workforce who are solving problems in wafer fabrication with which the decision is dealing. They are a subset of the whole workforces. Planning the knowledge workforce involves with neither hiring nor firing employees in the whole workforces. Knowledge workforce capacity (**KW-capacity**) is an appropriate metric for specifying the impact of the knowledge workforce on production in this thesis study for two reasons. First, in workforce planning the workforce volume is a major concern [e.g., Mody:1989, Dorroh-et-al:1994]. Second, only a team capable of performing the required tasks is taken as a unit of KW-capacity.

3.3.1 The Unit of KW-Capacity

The knowledge workforce team up to solve problems in wafer fabrication. Thus, a team is taken as the unit of KW-capacity. According to the work by Appleyard & Brown (2001), the team is composed of skilled engineers, technicians, and operators, and each occupation accounts for about $\frac{1}{3}$. Engineers act as team leaders since they are responsible for leading the processes of problem solving. Most of them have an undergraduate B.S. degree in engineering or science, and they focus on discovering why problems happened and how to handle them. Technicians, who usually have a technical high school or 2-year technical college diploma, assist engineers with troubleshooting, tool installation, and cleaning. Operators contributes less than the other two occupations. They usually have a high school diploma without attending college, and their roles are monitoring the process, collecting data, and conducting some simple statistical analyses. A team for solving problem could be teamed up in different ways, as described in Bailey (1998).

3.3.2 Training for Acquisition/Retention of KW-Capacity

KWA neither is a natural characteristic of workforce nor could be bought in the market or easily obtained by imitation. It is cultivated by practices of workforce management [e.g., Plonka (1997), Bailey (1998), Sattler & Sohoni (1999), Appleyard & Brown (2001), Anderson (2001), and Sumukadas & Sawhney (2004)]. Training is an effective practice for acquiring/retaining KW-capacity. The time interval between two successive opportunities of capacity adjustment, ΔT, equals the lead time of adjustment, which determines how many opportunities of KW-capacity adjustment exist over the PLC. During the PLC $[0, T]$ there are $\lfloor \frac{T}{\Delta T} \rfloor$ steps. The capacity adjustment at step i is determined at t_{i-1} (i.e., the beginning of the step), and it is fulfilled at t_i (i.e., the end of the step). Therefore, capacity options exist at t_i (for $i \in I = \{0, 1, 2, \ldots, \lfloor \frac{T}{\Delta T} \rfloor - 1\}$), and they will expire at $t_{\lfloor \frac{T}{\Delta T} \rfloor}$. c_i represents the KW-capacity delivered at t_i. It lasts for one step, and then it is updated to c_{i+1}.

The spillover of production knowledge and technologies from an old generation to a new one is limited, and the significant drop in productivity during generation replacements is an evidence [e.g., Klenow (1998), and Terwiesch & Xu (2004)]. Thus, for employees who are allocated to a new generation, the most of their previous knowledge becomes irrelevant to their new positions. An initial training could effectively recover the capability of knowledge workforce in the new positions. $N_{IT}(c_{i+1}|c_i)$ (N_{ITi} is the simplified notation in the remains of this thesis) is the number of teams which need the initial training at during $[t_i, t_{i+1})$, as in Equation (3.17).

$$N_{IT}(c_{i+1}|c_i) = \max(c_{i+1} - c_i, 0) \tag{3.17}$$

Equation (3.17) indicates that the initial training is conducted only in case of capacity expansion (i.e., $c_{i+1} > c_i$).

Employees, specially engineers in teams, have to be trained frequently although they have already received the initial training. This is because process changes in adoption of technology advances make the WK lose partially relevance to tasks they attempt to fulfill [Appleyard & Brown (2001)]. This type of training is referred to as the continuous training. This thesis assumes that a team without the necessary knowledge or skills has rare contributions to problem solving. The assumption is founded on a fact that the obsolescence of WK is relatively homogeneous in the PLC environment. $N_{CT}(c_{i+1}|c_i)$ (N_{CTi} is the simplified notation in the remains of this thesis) represents the number of teams which need the continuous training at during $[t_i, t_{i+1})$, as in Equation (3.18).

$$N_{CT}(c_{i+1}|c_i) = \min(c_i, c_{i+1}) \tag{3.18}$$

Equation (3.18) indicates that, when the KW-capacity needs an expansion, all of the current teams have to receive the continuous training, and the gap between c_i and c_{i+1} is filled by the initial training. If the KW-capacity needs an extraction, only a portion of the current teams have to receive the continuous training, and the remaining portion (i.e., $c_i - c_{i+1}$) is either sent to meet requests from other generations or becomes idle after the current jobs are finished.

$x_p(c_{i+1}|c_i, \eta_i)$ in Equation (3.19) (x_{pi} will be used as the simplifed notation in the remains of this thesis) represents the KW-capacity that are actually in problem solving during $[t_i, t_{i+1})$. x_{pi} is lower than c_i, usually, because the continuous training deducts a portion of c_i that otherwise can be used to generate immediate production profits.

$$x_p(c_{i+1}|c_i, \eta_i) = c_i - \eta_i \min(c_i, c_{i+1}) \tag{3.19}$$

η_i in Equation (3.19) represents η_t during $[t_i, t_{i+1})$. The expression of x_{pi} indicates that adoption of technology advances unanticipatedly variates the capability of knowledge workforce in problem solving. Thus, KWA is also manifested by the capability of generating desired KW-capacity when η_t is stochastic. Equation (3.19) additionally indicates that the adjustments of KW-capacity during the PLC are linked as a chain.

3.4 Quantifying KWA's Impact Elements on Production

KWA would benefits a dynamic system. Meanwhile, the system has to pay for it. Quantifying the elements of KWA impact on production is a necessary step towards optimization of KWA.

3.4.1 Characterizing The Role of Knowledge Workforce

Yield is a commonly used measure of production quality in semiconductor manufacturing, which is the product of line yield (the proportion of non-scrapped wafers) and die yield (the proportion of die on a non-scrapped wafer that pass tests). Yield manifests how deep the gap is between what have been specified in the process recipe and how the process is actually operated [e.g., Terwiesch & Xu (2004)]. The knowledge workforce would fill the gap through solving problems in transfer of cutting-edge technologies into products. Thus, yield can measures the role of knowledge workforce in production quality improvement. The impact of knowledge workforce on yield can be specified by a yield function wherein yield changes over KW-capacity

This thesis builds a yield function based on two notions. First, the marginal return of the knowledge workforce would decrease when KW-capacity increases [e.g., Mody (1989), and Dorroh et al. (1994)]. The reason of this is that opportunities of yield improvement are limited and will be exhausted progressively. Yield thus is a increasing concave function of KW-capacity. Second, the marginal return of the knowledge workforce drops substantially when the production ramps up, as indicated in relative work [e.g., Terwiesch & Bohn (2001)]. Therefore, this thesis assumes the yield function as

Equation (3.20).

$$y(c_{i+1}, x_{wi}|c_i, \eta_i) = 1 - e^{-\lambda_y \frac{x_{pi}}{x_{wi}}} = 1 - e^{-\lambda_y \frac{c_i - \eta_i \min(c_i, c_{i+1})}{x_{wi}}}. \tag{3.20}$$

λ_y in Equation (3.20) informs about the speed of yield improvement. x_{pi} is the KW-capacity in problem solving during $[t_i, t_{i+1})$, and Equation (3.19) has clarified the estimation of it. x_{wi} measures the number of wafer starts at that step, which represents the production scale. Equation (3.20) shows that KWA, as capacity options in a knowledge workforce, makes it possible to push yield to desired levels although the production scale has to be changed substantially to adapt to the unstable and volatile demand during the PLC. Equation (3.20) additionally indicates that the capacity options benefit yield management through compensating the unreliable performance of the knowledge workforce.

The way that this thesis models the impact of the knowledge workforce on production is different from the literature [e.g., Mody (1989), and Dorroh et al. (1994)]. For example, Mody (1989) formulates the reduction of variable cost as a results of cumulative investments on the knowledge workforce, as indicated in Equation (3.21).

$$r_t = \rho N_{pt} e^{-\int_0^t N_{p\tau} d\tau} \tag{3.21}$$

Wherein ρ is a parameter representing the difference in plant cells. v_c is the variable cost per wafter in this thesis, and the variable cost per chip is v, which is equal to $\frac{v_c}{y_t N_{IC}}$ (N_{IC} is the number of chips resided in a wafer). The variable cost models in Mody (1989) and in this thesis are compared in Table 3.1. To keep consistent in the comparison, subscript t is used in both models to represent the time index. Table 3.1 indicates that the variable cost is a decreasing convex function of the KW-capacity in both studies. However, the comparison further shows that Equation (3.20) is especially designed for the PLC environment since the yield function considers two additional issues. First, large production scales would depress the effectiveness of the knowledge workforce. Second, the instant KW-capacity N_{pt}, rather than the cumulative capacity over time $\int_0^t N_{p\tau} d\tau$, causes the yield improvement, indicating that successive process changes during the PLC discount the early investments on the knowledge workforce.

Table 3.1.
Comparing The Reduction of Variable Cost by Investments on KW-capacity

	Mody(1989)	**The Thesis**
$\frac{\partial v}{\partial x_{pt}}$	$-\rho x_{pt} e^{-\int_0^t x_{p\tau} d\tau} < 0$	$-\frac{\lambda_y v_c}{x_{wt} N_{IC} y_t^2} e^{-\lambda_y \frac{x_{pt}}{x_{wt}}} < 0$
$\frac{\partial^2 v}{\partial x_{pt}^2}$	$\rho(x_{pt}^2 - 1) e^{-\int_0^t x_{p\tau} d\tau} \geq 0$	$\frac{\lambda_y^2 v_c (2-y_t)}{x_{wt}^2 N_{IC} y_t^3} e^{-\lambda_y \frac{x_{pt}}{x_{wt}}} > 0$

3.4.2 Costs in Acquisition/Retention of KW-Capacity

Identifying costs spent in generation of KWA helps keep rationality in utilization of KWA. Based on the work by Appleyard & Brown (2001), this thesis assumes that individuals who are dispatched to a new generation receive an one-month initial training just before ahead of undertaking new responsibility, and engineers who are in charge of problem solving and will continue the responsibility spend one week in the continuous training per month on average (i.e., $E[\eta_t] = 25\%$). Costs involved in training, referred to as KW-capacity acquisition/retention costs, are an important component of the costs in wafer fabrication, as indicated in Figure 3.4. KW-capacity acquisition/retention costs are separated into two components. The first component includes training expenses, and the second component consists of production profit losses since training occupies production resources (e.g., employees and equipment) that otherwise can be used to generate immediate production profits. The costs are the payment for KWA, and they will be paid off in two approaches. First, the costs make the expensive fixed costs recovered quickly. A state-of-art fab plant costs \$3.5 billions or even more, so semiconductor manufacturers have a high operating leverage and require massive economies of scale. Second,the costs of KWA substantially lower the variable production cost through improving production quality.

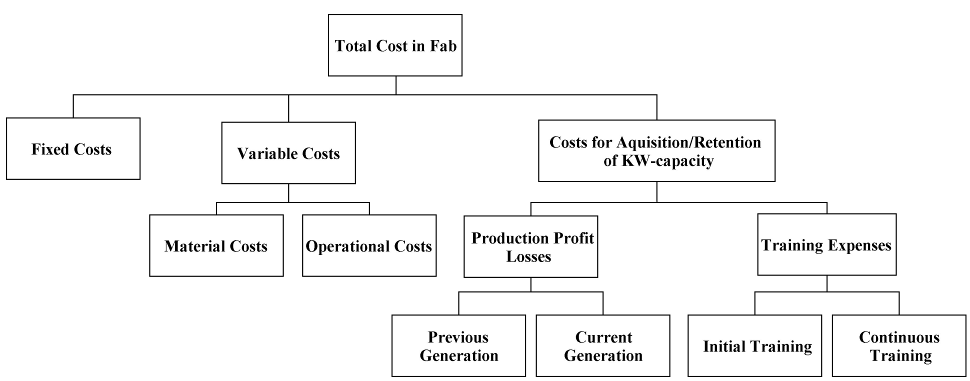


Fig. 3.4. A Classification of Costs in Wafer Fabrication

This thesis assumes that every team allocated to a new generation is from the previous generation. All employees in the team, including operators, technicians and engineers, receive an initial training before they serve the new generation. Employees in the initial training can not take the previous responsibility, and thus a production profit loss in the previous generation is caused, as calculated in Equation (3.22).

$$C^{IP}(c_{i+1}|c_i) = a_{1i}^{IP}\left(e^{a_{2i}^{IP}N_{ITi}} - 1\right) \tag{3.22}$$

$C^{IP}(c_{i+1}|c_i)$ in Equation (3.22) will be simply notated as C_i^{IP} is the remains of this thesis. Appendix F shows how Equation (3.22) and the parameters a_{1i}^{IP} and a_{2i}^{IP} are derived. Equation (F.9) shows that a_{1i}^{IP} decreases quickly over time, and Equation (F.10) indicates that a_{2i}^{IP} increases dramatically as time elapses. Thus, C_i^{IP}, the production profit loss caused by the initial training, is observed to decrease and be more curved when moving along the PLC, as displayed in Figure 3.5 which illustrates C_i^{IP} at three different time in the PLC. The figure indicates that to obtain a new unit of KW-capacity in the early PLC is more expensive than in the late PLC, and to instantly and substantially raise KW-capacity will become more and more difficult along the PLC. The characteristic of C_i^{IP} emphasize the importance of planning KW-capacity strategically over the PLC. Suddenly raising or lowering KW-capacity due to the short sight would hurt production profitability.

Unlike the initial training, the continuous training results in a production profit loss in the current generation, which has been indicated by the difference between c_i, the available KW-capacity, and x_{pi}, the actual KW-capacity in problem solving in evaluation of periodic revenue. Thus, to evaluate this cost explicitly is not a necessity.

Except for the losses of production, training programs themselves involve some expenses. $C^{IT}(c_{i+1}|c_i)$ (C_i^{IT} is the simplified notation in the remains of this thesis) and

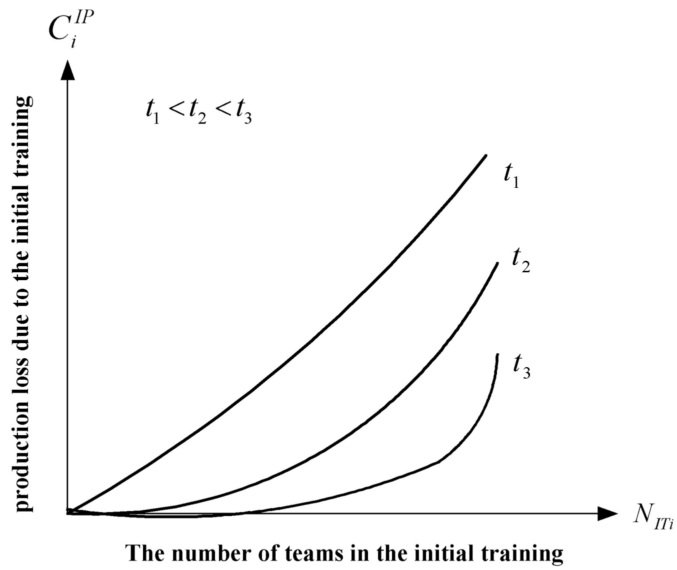


Fig. 3.5. Production Profit Loss due to The Initial Training

$C^{CT}(c_{i+1}|c_i)$ (C_i^{CT} is the simplified notation) represent the expenses of initial training and of continuous training, respectively. This thesis formulates them based on three notions. First, the training program at a large scale is more complex to be handled than at a small scale. Second, workforce heterogeneity is more severe in a large group of employees than in a small group. Third, the KW-capacity that an organization can obtain is not infinite. Thus, it is reasonable to assume increasing marginal costs of training. The more sever the three abovementioned issues, the larger the marginal costs. This thesis thereby assumes C_i^{IT} and C_i^{CT} as quadratic functions, as illustrated in Equations (3.23) and (3.24).

$$C^{IT}(c_{i+1}|c_i) = a_0^{IT} sign(N_{ITi}) + a_1^{IT} N_{ITi} + a_2^{IT} N_{ITi}^2, \tag{3.23}$$

wherein $a^{IT}_{(.)}$ are nonnegative parameters of the initial training cost function.

$$C^{CT}(c_{i+1}|c_i) = a_0^{CT} sign(N_{CTi}) + a_1^{CT} N_{CTi} + a_2^{CT} N_{CTi}^2, \tag{3.24}$$

wherein $a^{CT}_{(.)}$ are nonnegative parameters of the continuous training cost function.

3.5 Optimization of KWA w.r.t. Demand Changes

To facilitate the presentation, this thesis first takes only market demand as the underlying stochastic process that KWA intends to respond to. So, η_t is assumed as deterministic during the PLC in this section. This assumption will be relaxed in the next section.

3.5.1 The Optimization Problem

Agility should not be simply interpreted as short response time, low costs, sufficient robustness, broad scope or other metrics [Dove (1995)]. A manufacturer will not be competitive if it has to pay an overwhelming expense for emphasizing too much on just one aspect. Agility is a balance among them at a strategic level. For a profit-driven manufacturer, to maximize the expected NPV (or the expected NPV increment) through optimization of KWA meets the goal of achieving long-term competition and profits.

This thesis models KWA as capacity options in a knowledge workforce, so KW-capacity is a major decision variable. To be specific, confronting unanticipated demand changes, the decision maker has to at least periodically review how many units of KW-capacity should be built for the subsequent step so that demand at that step is met properly for pursuing long-term profitability. To plan KW-capacity for the subsequent step, the decision maker has to additionally plan the capacity for any level of demand at any remaining step because of two reasons. First, the demand forecast is in a form of probability distribution and the variance of demand increases linearly over time. Second, KW-capacity adjustments over the PLC are dependent.

The decision in optimization indicates that KWA is American options which have no closed form solutions in optimization. Thus, the optimization of KWA is accomplished numerically. This thesis pursues the optimization of KWA under demand uncertainty using the RO valuation in below. It first approximately presents the distribution of future demand using a binomial lattice because it is straightforward when the option valuation is complex. After that a standard backward dynamic programming (**DP**) is conducted on the binomial lattice. The backward DP optimizes capacity options by maximizing the expected remaining value at every node of the lattice and for any possibility of KW-capacity, ultimately leading to the maximization of the expected NPV.

3.5.2 The Optimization Scheme

The scheme of optimizing KWA under demand uncertainty can be named as the repeated knowledge workforce planning because accuracy of the demand forecast is conditioning on how much information about T_m the decision maker has. Decision bias may be reduced by repeating capacity planning for the remainder of PLC when Bayesian estimation updates the information about T_m. The pseudocode of the optimization procedures is in below:

1. To find where capacity options exist

estimate the decision horizon T_D;

determine the interval between capacity adjustments ΔT;

capacity options exist at t_i (for $i = 0, 1, \ldots, N_D - 1$; $N_D = \left\lfloor \frac{T_D}{\Delta_T} \right\rfloor$).

2. **for** $i := 0$ **to** $N_D - 1$

observe D_i;

obtain $\hat{T}_{mi}$, the Bayesian estimate of T_m, if $i > 0$;

build lattice B_i;

find optimal capacity c^*_{i+1} with backward DP on B_i;

endfor

The decision horizon, T_D, is estimated by searching for a point in the PLC whence no further profit can be realized due to the price erosion. The quick erosion of sales price over the PLC is another clear phenomenon over the PLC. The sales price for each generation of product is high at the beginning of the PLC, but it falls rapidly and monotonically during the PLC [e.g., Mody & Wheeler (1987), and Siebert (2003)]. This thesis formulates the sales price in Equation 3.25.

$$p_t = p_0 \exp\left(-\lambda_p t\right) \tag{3.25}$$

p_0 in Equation (3.25) is the initial price, and λ_p is the rate of price erosion. The sales price in Equation 3.25 is a decreasing function of time but at a reduced pace $\left(\frac{\partial p_t}{\partial t} < 0, \frac{\partial^2 p_t}{\partial t^2} > 0\right)$, which consists with the notion in Siebert (2003). This thesis assumes that the decision maker stops producing this generation of product after T_D, which means he/she only needs to consider decisions before T_D.

The lead time of the initial training, ΔT, is taken as the step size on the time index in approximation of demand, so how many opportunities of KW-capacity adjustment exist during the PLC depends on how long ΔT is. ΔT is about one month, relative short compared to the PLC which is usually 10 years on average.

A unique lattice B_i is constructed for each opportunity of KW-capacity adjustment, and all the lattices form a lattice topology $B_I = \{B_i | i \in I = \{0, 1, \ldots, N_D - 1\}\}$. Construction of B_I over the PLC uses the newly updated Bayesian estimate of T_m, so the time horizon of B_i ($\forall i \in I$) is estimated in Equation (3.26).

$$T_{Di} = \min(T_D, 2\hat{T}_{mi}) - i\Delta T \tag{3.26}$$

Correspondingly, the number of steps in B_i is in Equation (3.27).

$$N_{Di} = \left\lfloor \frac{T_{Di}}{\Delta T} \right\rfloor = \left\lfloor \frac{\min(T_D, 2\hat{T}_{mi})}{\Delta T} \right\rfloor - i \tag{3.27}$$

$\hat{T}_{mi}$ In Equations (3.26) and (3.27) is assumed as the middle of the PLC. $2\hat{T}_{mi}$ could be shorter than T_D, so $\min(T_D, 2\hat{T}_{mi}) - i\Delta T$ is the proper estimate of the remainder decision horizon from t_i.

The backward DP is repeated on B_I. That is, at t_0, the beginning of the PLC, KW-capacity is decided for all demand levels at any remaining steps based on lattice B_0 (μ_{T_m} is the best point estimate of T_m given that D_0 is the only demand information available). At t_i (for $i = 1, 2, \ldots, N_D - 1$), the newly coming demand D_i makes it possible to obtain $\hat{T}_{mi}$ using Bayesian Estimation. Then, B_i starts from D_i and is based on $\hat{T}_{mi}$, whereon KW-capacity is re-decided for all demand levels at any remaining steps.

3.5.3 Approximating D_t as A Binomial Lattice

Parameters of B_I are functions of drift rate in demand, μ_t, due to the adoption of modified risk-neutral valuation principle. The time dependency of μ_t will lead to a variable time step if demand is approximated using the popular CRR lattice (see Cox et al. (1979)). Approximation demand using a lattice with a variable step not only violates the design of KWA but complicates the RO valuation. This thesis thus adopts the JR lattice presented by Jarrow & Rudd (1983) to cope with the time dependency of the drift rate. The drift rate in the JR lattice is represented by demand levels rather than by the risk-neutral probability. As a result, a lattice with a constant step is capable of approximating Equation (3.1) (A comprehensive comparison of lattices in the American options valuation is discussed by Broadie & Detemple (2004)).

Figure (3.6) illustrates lattice B_i. The lattice starts at D_i, the desecrate demand coming at t_i. At t_{i_k} ($\forall k \in K_i = \{0, 1, \ldots, N_{Di} - 1\}$), the end of step k on B_i (it is the end of step $i + k$ during the PLC as well), B_i has $k + 1$ unique levels of demand, which are denoted as $D_{i_k j}$ ($\forall j \in J_k = \{0, 1, \ldots, k\}$) in a descending order. The ratio of demand increase and decrease at t_{i_k} are calculated in Equation (3.28).

$$
\begin{aligned}
u_{i_k} &= \frac{D_{i_{k+1} j}}{D_{i_k j}} = e^{\left(\frac{\beta^2}{\hat{T}_{mi}} - \frac{\beta^2}{\hat{T}^2_{mi}}\left(t_{i_k} + \frac{\Delta T}{2}\right) - \frac{1}{2}\sigma^2 - \lambda\sigma\right)\Delta T + \sigma\sqrt{\Delta T}} \\
d_{i_k} &= \frac{D_{i_{(k+1)}(j+1)}}{D_{i_k j}} = e^{\left(\frac{\beta^2}{\hat{T}_{mi}} - \frac{\beta^2}{\hat{T}^2_{mi}}\left(t_{i_k} + \frac{\Delta T}{2}\right) - \frac{1}{2}\sigma^2 - \lambda\sigma\right)\Delta T - \sigma\sqrt{\Delta T}}
\end{aligned}
\tag{3.28}
$$

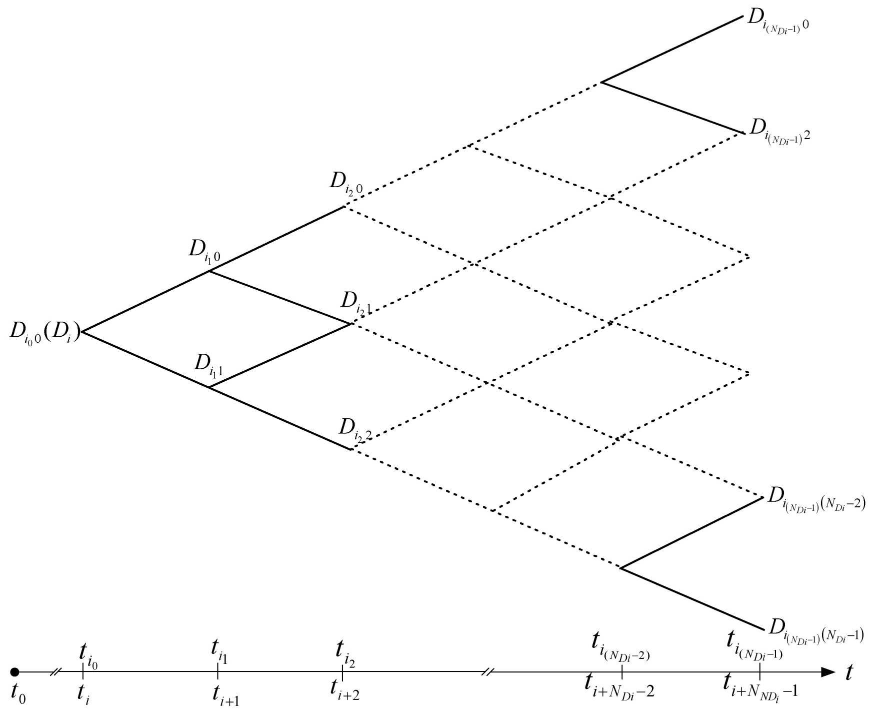


Fig. 3.6. Lattice B_i Representing The Future Demand Since D_i

The risk neutral probability is evaluated in Equation (3.29).

$$P_{rn} = \frac{e^{0.5\sigma^2 \Delta T} - e^{-\sigma \Delta T}}{e^{\sigma \Delta T} - e^{-\sigma \Delta T}} \tag{3.29}$$

P_{rn} in Equation (3.10) approaches to 0.5 as ΔT goes to zero. The choices of u_{i_k}, d_{i_k}, and P_{rn} as above insure that the binomial process has the same first two moments as the lognormal process in Equation (3.1). Thus, when demand D_i is observed, the future demand since then is properly approximated by the binomial process $D_{i_k j}$ in Equation

(3.30).

$$D_{i_k j} = D_i e^{\left(\frac{\beta^2}{\hat{T}_{mi}} - \frac{\beta^2}{\hat{T}_{mi}^2}\left(t_i + \frac{k\Delta T}{2}\right) - \frac{\sigma^2}{2} - \lambda\sigma\right)k\Delta T + (k-2j)\sigma\sqrt{\Delta T}} \qquad \forall k \in K_i, j \in J_k \tag{3.30}$$

3.5.4 RO Valuation on A Binomial Lattice

At $t_i (\forall i \in I)$, the optimal capacity, c_i^*, accompanying the arrival of D_i, becomes available. Based on c_i^* and D_i, the optimal capacity for the subsequent step, c_{i+1}^*, can be attained within the action space C ($C = \{0, 1, \ldots, U_C\}$ is a countable finite set) using the RO valuation.

The RO valuation is a standard backward DP procedure, which is composed of the optimizations of a well-defined valuation function in a backward order. The optimization at t_{i_k} ($\forall k \in K_i$) is based on two state variables, D_{i_k} and c_{i_k}, which are demand and the KW-capacity at t_{i_k} respectively. Since B_i enumerates all levels of $D_{i_k} (\forall k \in K_i)$, the DP procedure on B_i is equivalent to maximizing the valuation function at any node at t_{i_k} (for $k = N_{Di} - 1, N_{Di} - 2, \ldots, 1, 0$) and any possible value of c_{i_k}. Equation (3.31) expresses the valuation function at t_{i_k}, which shows that decisions are the capacity for the subsequent step, $c_{i_{k+1}}$ and the current production scale, x_{wi_k}.

$$\begin{aligned} V\left(c_{i_{k+1}}, x_{wi_k} \mid D_{i_k}, c_{i_k}\right) = {} & p_{t_{i_k}} \min\left(D_{i_k}, N_{IC} x_{wi_k} y\left(c_{i_{k+1}}, x_{wi_k} \mid c_{i_k}\right)\right) \\ & - c_v x_{wi_k} - C^{IP}(c_{i_{k+1}} | c_{i_k}) - C^{IT}(c_{i_{k+1}} | c_{i_k}) - C^{CT}(c_{i_{k+1}} | c_{i_k}) \\ & - EV\left(D_{i_k}, c_{i_{k+1}}\right) \end{aligned} \tag{3.31}$$

$$D_{i_k} := D_{i_k j} \quad \exists i \in I, \exists k \in K_i, \forall j \in J_k; \qquad c_{i_k} := \forall c \in C$$

The valuation function in Equation (3.31) calculates the expected remaining value at t_{i_k} given the decisions $c_{i_{k+1}}$ and x_{wi_k} made in the situation identified by states D_{i_k} and c_{i_k}. The valuation function indicates that capacity options in the knowledge workforce at t_{i_k} provide the opportunity to manipulate the expected remaining value. $V\left(c_{i_{k+1}}, x_{wi_k}|D_{i_k}, c_{i_k}\right)$ is composed of three parts. The first part is the periodic revenue during $[t_{i_k}, t_{i_{k+1}})$, which is the product of sales price $p_{t_{i_k}}$ and the periodic sales volume $\min\left(D_{i_k}, N_{IC}x_{wi_k}y_{i_k}\right)$. The second part consists of all explicit periodic variable costs, including the production variable cost $c_v x_{wi_k}$, the production profit loss caused by the initial training $C_{i_k}^{IP}$, the expense of the initial training $C_{i_k}^{IT}$, and the expense of the continuous training $C_{i_k}^{CT}$. The last part $EV\left(D_{i_k}, c_{i_{k+1}}\right)$ is the expected maximum future value given the current demand D_{i_k} and KW-capacity for the subsequent step $c_{i_{k+1}}$, as evaluated in Equation (3.32).

$$\begin{aligned} EV\left(D_{i_k}, c_{i_{k+1}}\right) =& e^{-r_f \Delta T}\left[P_{rn}V^*\left(u_{i_k}D_{i_k}, c_{i_{k+1}}\right)\right. \\ & \left. +(1-P_{rn})V^*\left(d_{i_k}D_{i_k}, c_{i_{k+1}}\right)\right] \end{aligned} \tag{3.32}$$

$$D_{i_k} := D_{i_k j}\exists i \in I, \exists k \in K_i, \forall j \in J_k; \qquad c_{i_k} := \forall c \in C$$

V^* in Equation (3.32) represents the maximum of valuation function at $t_{i_{k+1}}$ conditioning on the demand at t_{i_k} and KW-capacity at $t_{i_{k+1}}$. Decisions on B_i ($\forall i \in I$) form a chain because Equations (3.31) and (3.32) indicate that the maximization of $V\left(c_{i_{k+1}}, x_{wi_k}|D_{i_k}, c_{i_k}\right)$ pertains to $V^*\left(u_{i_k}D_{i_k}, c_{i_{k+1}}\right)$ and $V^*\left(d_{i_k}D_{i_k j}, c_{i_{k+1}}\right)$. Backward recursion on B_i thus is a necessity for obtaining c^*_{i+1}.

The Backward recursion on B_i ($\forall i \in I$) involves determining the optimal capacity options in the knowledge workforce, as illustrated in Equation (3.33), through maximizing the valuation function in a back order (i.e., $k = N_{Di} - 1, N_{Di} - 2, \ldots, 0$).

$$
\begin{aligned}
V^*(D_{i_k}, c_{i_k}) = & \max_{x_{wi_k} \in W, c_{i_{k+1}} \in C} \left\{ V\left(c_{i_{k+1}}, x_{wi_k} | D_{i_k}, c_{i_k}\right)\right\} \\
& = p_{t_{i_k}} \min\left(D_{i_k}, N_{IC} c^*_{wi_k} y(c^*_{i_{k+1}}, x^*_{wi_k} | c_{i_k})\right) \\
& \quad - c_v x^*_{wi_k} - C^{IP}\left(c^*_{i_{k+1}} | c_{i_k}\right) - C^{IT}\left(c^*_{i_{k+1}} | c_{i_k}\right) - C^{CT}\left(c^*_{i_{k+1}} | c_{i_k}\right) \\
& \quad - EV\left(D_{i_k}, c^*_{i_{k+1}}\right)
\end{aligned}
\tag{3.33}
$$

$$
D_{i_k} := D_{i_k j} \quad \exists i \in I, \exists k \in K_i, \forall j \in J_k; \qquad c_{i_k} := \forall c \in C
$$

$c_{i^*_{k+1}}$ and $x^*_{wi_k}$ in Equation (3.33) are the decision which maximizes the valuation function in Equation (3.31). The backward recursion on B_i starts from $t_{i_{(N_{Di}-1)}}$, the beginning of last step wherein the last chance of KW-capacity adjustment resides. Capacity options will expire after that, so the expected future value at $t_{i_{(N_{Di}-1)}}$ is zero, and no additional capacity should be further invested (i.e., $c^*_{N_{Di}} = 0$). c^*_{i+1} will be obtained at the end of the backward recursion.

Appendix G justifies that $x^*_{wi_k}$ is a function of $c_{i_{k+1}}$. That is, $x^*_{wi_k} = g^Z(c_{i_{k+1}})$. Thus, the backward DP on B_i is reduced to have only one decision variable c_{i_k} ($\forall k \in K_i$), and Equation (3.33) turns to Equation (3.34), correspondingly.

$$
\begin{aligned}
V^*(D_{i_k}, c_{i_k}) &= \max_{c_{i_{k+1}} \in C} \left\{ V\left(c_{i_{k+1}}, g^Z(c_{i_{k+1}}) | D_{i_k}, c_{i_k} \right) \right\} \\
&= p_{t_{i_k}} \min\left(D_{i_k}, N_{IC} g^Z(c^*_{i_{k+1}}) y(c^*_{i_{k+1}}, g^Z(c^*_{i_{k+1}}) | c_{i_k}) \right) \\
&- c_v g^Z(c^*_{i_{k+1}}) - C^{IP}\left(c^*_{i_{k+1}} | c_{i_k} \right) - C^{IT}\left(c^*_{i_{k+1}} | c_{i_k} \right) - C^{CT}\left(c^*_{i_{k+1}} | c_{i_k} \right) \\
&- EV\left(D_(i_k), c^*_{i_{k+1}} \right)
\end{aligned}
\tag{3.34}
$$

$$
D_{i_k} := D_{i_k j} \quad \exists i \in I, \exists k \in K_i, \forall j \in J_k; \qquad c_{i_k} := \forall c \in C
$$

3.5.5 Improving Computational Efficiency of DP Procedure

Computational inefficiency of DP procedure is a potential problem that the work of this thesis confronts. The RO valuation repeats N_D times, each time on a unique lattice B_i. B_i has $\frac{N_{Di}(N_{Di}+1)}{2}$ nodes, on each of which the valuation function will be evaluated $(U_C + 1)^2$ times. If the time spent on evaluating the valuation function for one time is taken as the unit of computational effort, the computational effort of the RO valuation on B_I is $(U_C + 1)^2 \sum_{i \in I} \frac{N_{Di}(N_{Di}+1)}{2}$. Thus, the computational complexity is $O(U_C^2 N_D^3)$. Computational complexity can be reduced substantially either by reducing the action space C or by enlarging the step size of B_I. To enlarge the step size is not realistic in this thesis. On one hand, the step size of B_I has its own physical meaning, so to change it is impractical. One the other hand, to enlarge the step size would reduce the opportunities of KW-capacity adjustments, which conflicts with the essence of KWA.

Therefore, to consider less possibilities in C is the way of speeding up the DP procedure, and this idea can be realized by making a good guest on the optimal decision.

On one hand, C as the full decision space of $c_{i_{k+1}}$ can be replaced by a reduced decision space, $[\max(0, c_{i_k} - \Delta c), \min(U_C, c_{i_k} + \Delta c)]$, wherein Δc is a small positive integer representing the maximum deviation of $c_{i_{k+1}}$ from c_{i_k}. This substitution is based on a fact that $c^*_{i_{k+1}}$ is highly possible near c_{i_k} since adjusting KW-capacity substantially either makes the capacity expansion cost rises sharply or leads to severe loss from KW-capacity insufficiency. On the other hand, C as the full state space of c_{i_k} can be replaced by a reduced state space $[0, \min(U_C, \zeta D_{i_k})]$, wherein ζ is a positive parameter for pertaining the demand unit to the capacity unit. The substitution is based on a notion that $c^*_{i_k}$ is highly relevant to demand for avoiding the expensive holding cost from the excessive KW-capacity and immediate the loss from KW-capacity insufficiency. ζ is chosen to insure a sufficiently high yield for satisfying demand. Of course, to immediately reduce KW-capacity to 0 is a possibility. Therefore, $[0, \min(U_C, \zeta D)]$ is a subset of C with a higher chance of containing $c^*_{i_k}$ than C.

Δc and ζ can be determined in simulation studies. Solution accuracy will be improved at a reduced rate when Δc increases, which can be discovered in a simulation study. Δc thus can be determined according to the acceptable level of solution accuracy. ζ can be obtained in a similar approach.

Figure 3.7 displays the reduced decision/state space and the full decision/state C on two unique nodes in a binomial lattice to illustrate the difference. The figure shows that the reduced state space varies with demand, and the reduced action space is much narrower than C. The computational effort is reduced by $\left(1-2\frac{\Delta c}{U_C+1}\right)\times 100\%$ at least, correspondingly.

3.6 Optimization KWA w.r.t. Demand Changes and WK Dynamics

Frequent, unexpected jumps of η_t manifest the major source of KW dynamics in adoption of technology advances. η_t is another underlying process containing some interests of KWA. This section considers uncertainties in D_t and in η_t when optimizing KWA. To focus on how KWA reacts to η_t jumps, this section assumes that σ_η in Equation (3.16) equals zero or $\sigma_\eta \ll \lambda_\eta r_\eta^2$. η_t thus turns to be Equation (3.35).

$$\eta_t = e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\left(\eta_m - \frac{\lambda_\eta r_\eta}{\alpha_\eta}\right) + r_\eta \int_0^t e^{\alpha_\eta (s-t)} dN_s \tag{3.35}$$

The optimization that additionally considers the underlying process in Equation (3.35) does not substantially change the major framework in the previous section.

3.6.1 Approximating η_t as A Binomial Tree

Binomial process could be a reasonable discrete approximate of Poisson process if the time step is small enough (see Appendix H). Assuming that $[0,t)$ is divided into l equal intervals in length of $\Delta T'$, and defining ω as $e^{-\alpha_\eta \Delta T'}$, η_l in Equation (3.36) is the discrete approximate of η_t.

$$\eta_l = \overline{\eta}_l + r_\eta \overrightarrow{z_l} \cdot \overrightarrow{\omega_l} \tag{3.36}$$

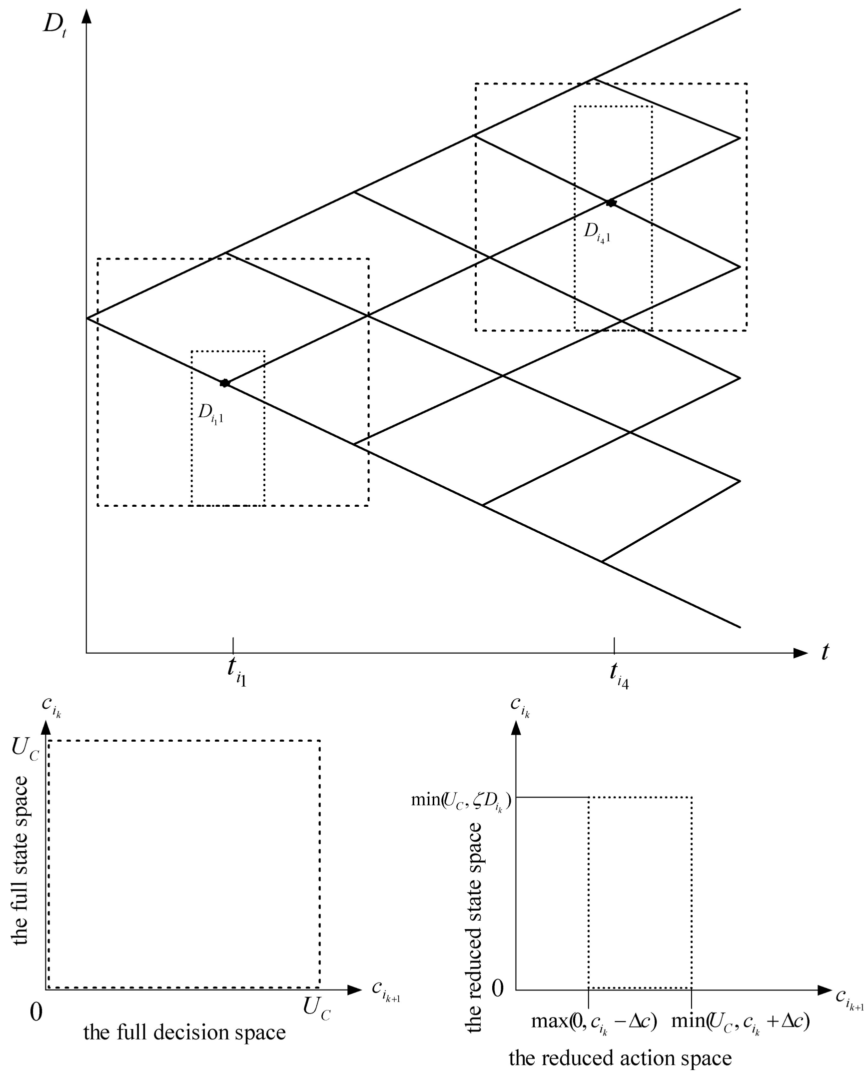


Fig. 3.7. Replacing C with The Reduced Decision/State Space

wherein

$$\overline{\eta}_l = \omega^l \eta_0 + \left(1 - \omega^l\right)\left(\eta_m - \frac{\omega r_\eta \lambda_\eta \Delta T'}{1-\omega}\right), \tag{3.37}$$

$$\overrightarrow{z}_l = [z_1, z_2 \ldots, z_l], \tag{3.38}$$

$$\overrightarrow{\omega}_l = [\omega^l, \omega^{l-1}, \ldots, \omega]. \tag{3.39}$$

Equation (3.36) shows that η_l is separated into two parts. $\overline{\eta}_l$ is the deterministic trend of η_l. $r_\eta \overrightarrow{z}_l \cdot \overrightarrow{\omega}_l$ represents the stochasticity of η_l. z_k ($k = K_l = \{1, 2, \ldots, l\}$) in Equation (3.36) are independent and identical-distributed binomial variables for identifying the status of jumps in the past l steps (e.g., $z_k = 1$ indicates a jump happens in the kth step, and no jump happens if $z_k = 0$). Thus, $\overrightarrow{z}_l$ is a vector variable which records the history of jumps up to t. The magnitude of a jump will drop a little because of the learning effect, which is manifested by mean-reverting of η_t after jump. ω measures the residual effect of a jump in one step. For example, the residual effect of a jump happened in the kth step ahead of t is reduced by a factor ω^k. Thus, vector $\overrightarrow{\omega}_l$ specifies the residual level of any possible jump up to t. $r_\eta \overrightarrow{z_l} \cdot \overrightarrow{\omega_l}$ thereby represents the accumulative residual effect of η jumps up to t.

Vector $\overrightarrow{\omega}_l$ in Equation (3.36) has l unique elements and binomial variable vector $\overrightarrow{z}_l$ has 2^l possible outcomes, so the dot product of them gives 2^l possibilities. Thus, Equation (3.36) has 2^l possible outcomes, and it is equivalent to a binomial tree, as Figure 3.8 illustrates. The binomial tree enumerates the 2^l unique levels of η_l. If a jump happens in the interval of $[t_{l'-1}, t_{l'})$ (i.e., the lth step), η_{ln}, the nth level of η_l, either

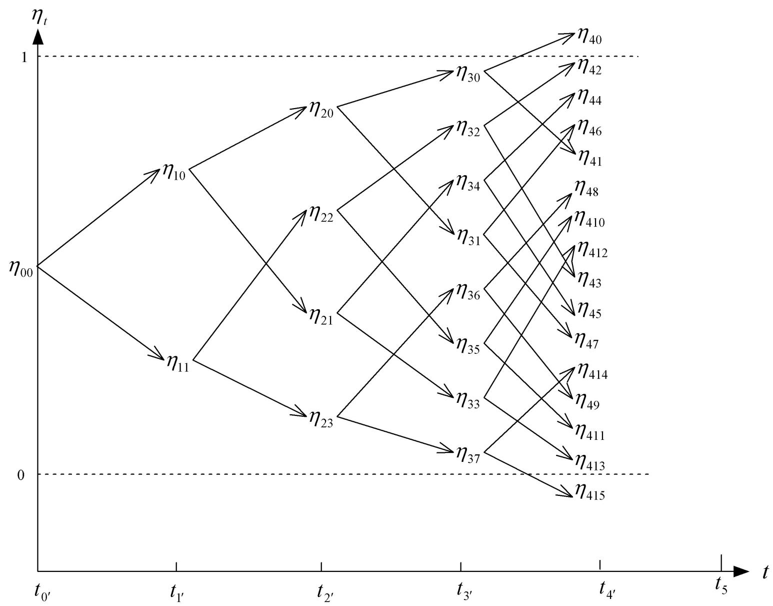


Fig. 3.8. A Binomial Tree Approximating The Risk-Neutralized η_t

jumps to $\eta_{(l+1)(2n)}$ or goes to $\eta_{(l+1)(2n+1)}$, as indicated in Equation (3.40).

$$\begin{aligned}
\eta_l^u &= \omega\eta_l + (1-\omega)\,\eta_m - \left(\omega r_\eta \lambda_\eta \Delta T'\right) + \omega r_\eta \\
\eta_l^d &= \omega\eta_l + (1-\omega)\,\eta_m - \left(\omega r_\eta \lambda_\eta \Delta T'\right)
\end{aligned} \tag{3.40}$$

$$\eta_l := \eta_{ln} \qquad n = 0, 1, \ldots, 2^l - 1; \qquad \eta_l^u := \eta_{(l+1)(2n)}, \quad \eta_l^d := \eta_{(l+1)(2n+1)}$$

η_t is bounded within $[0, 1]$, as indicated in Figure 3.8. Thus, P_η, the probability whereby η_l jumps to η_l^u, is defined in Equation (3.41).

$$P_\eta = \begin{cases} 0 & \eta_l^u > 1 \\ 1 & \eta_l^d < 0 \\ \lambda_\eta \Delta T' & otherwise \end{cases} \tag{3.41}$$

3.6.2 Replacing The Binomial Tree with A Group-Based Hybrid Tree

Binomial tree is computationally inefficient because the computational complexity of a N-steps binomial tree is $O(2^N)$. However, the variance of η_t is bounded asymptotically, as stated in Section 3.2. To represents such a variance using a binomial tree which propagates quickly is not a necessity. This thesis suggests to replace the binomial tree with a hybrid tree. Major difference between the binomial tree and the hybrid tree is the way of choosing tree nodes for presenting uncertainty, which is similar to the selection of nodes for representing subspaces in the branch and bound algorithm [Lawler & Wood (1966)]. Some similar nodes in the binomial tree are combined and some nodes with small values are approximated by zero, generating the hybrid tree. Thus, nodes of the hybrid tree represent the state space more efficient and make the optimization problem solved quickly.

The tree in Figure 3.8 enumerate 2^l possibilities of $\eta_{t_{l'}}$. The speed whereby the binomial tree propagates at $t_{l'}$ is determined by the number of unique elements in the sequence $S_l(\omega) = \left\{\omega, \omega^2, \ldots, \omega^l\right\}$, as indicated in Equation (3.36). Although sequence $S_l(\omega)$ has l unique elements, many of them just exhibit a trivial change when l is large because the sequence will converge if l remains growing. This suggests to slow down the propagation of the binomial tree through reducing the number of unique elements in $S_l(\omega)$ when l is large. The result of this action is mergence of tree nodes. Further, sequence $S_l(\omega)$ converges to zero if l is large enough, which indicates some elements in the sequence can be approximated by zero when l remains growing. Accordingly, the binomial tree stops growing, ultimately. These ideas help reduce the computational complexity of the binomial three, yet without severely impairing the solution accuracy.

Appendix I justifies that a N_D-steps Binomial tree can be replaced by a three-phases hybrid tree, approximately. That is, there exists two integers N_T and N_L, which satisfy $0 < N_T \leq N_L < N_D$ and separate the PLC into three phases. Each phase has a unique structure for representing the jump process. A hybrid tree that represents $\overrightarrow{z_l} \cdot \overrightarrow{\omega_l}$, the unpredictability of $\eta_{t_{l'}}$ (for $0 \leq l < N_D$), is illustrated in Figure 3.9. The first phase

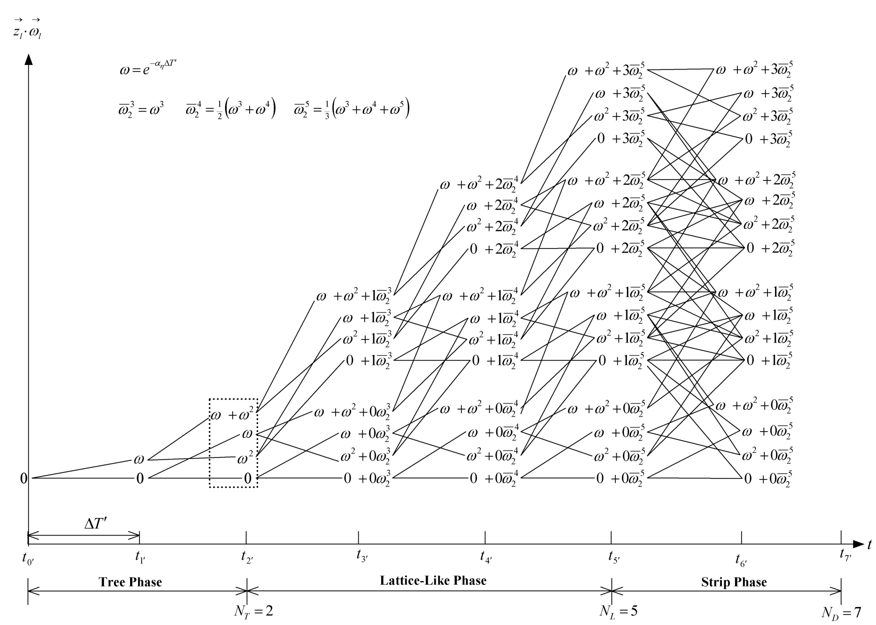


Fig. 3.9. A Hybrid Tree Representing The Unpredictability of η_t

of the hybrid tree consists of the first two steps, and it is a binomial tree. The steps three, four, and five belong to the lattice-like phase, whereon some nodes of the binomial three are combined. The strip phase has the last two steps, and the number of nodes stops growing in this phase. Neither the lattice-like phase nor the strip phase is a necessity, so a three-phases hybrid tree is a generalized case.

Nodes on the hybrid tree can be grouped up based on similarity, forming a group-based hybrid tree. Figure 3.10 displays the grouped hybrid tree in Figure 3.9. The

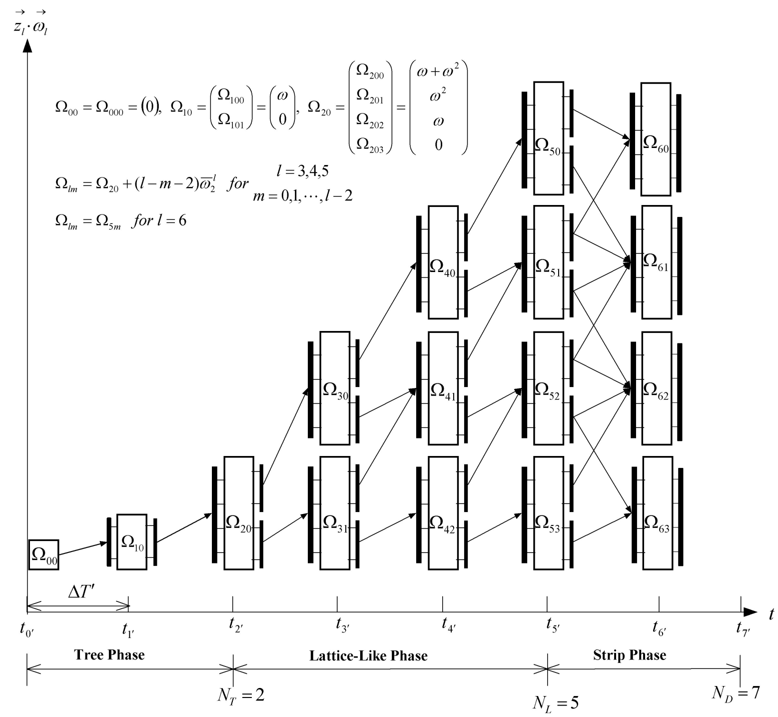


Fig. 3.10. The Group-Based Hybrid Tree

group-based hybrid tree is the same as the hybrid tree except that it uses a more clear notation system, which benefits the analysis of complicated cases. Nodes of the group-based hybrid tree which represents $\overrightarrow{z}_l \cdot \overrightarrow{\omega}_l$ are denoted as Ω_{lmn}, wherein the three subscripts identify the node position. The first subscript is the discrete time index, the second one is the between-group index, and the last one is the within-group index. For example, Ω_{lmn} represents the nth element in the mth group at $t_{l'}$. Correspondingly, Ω_{lm} is the vector containing all the elements in the mth group, and Ω_l is the vector consisting of all the groups/elements at the lth step. The hybrid three has only one group in the tree phase, the number of group increases one in every step in the lattice-like phase, and in the strip phase no additional group is generated, as illustrated in Figure 3.10.

The group-based hybrid tree for representing $\overrightarrow{z}_l \cdot \overrightarrow{\omega}_l$ is formulated in below and is illustrated in Figure 3.10. The hybrid tree starts from one group with one element zero, that is,

$$\Omega_0 = (\Omega_{00}) = (\Omega_{000}) = (0). \tag{3.42}$$

In the tree phase, the group size is 2^l at $t_{l'}$, as indicated in Equation (3.43).

$$\Omega_l = \begin{pmatrix} \Omega_{l-1} + \omega^l \\ \\ \Omega_{l-1} \end{pmatrix} = (\Omega_{l0}) = \begin{pmatrix} \Omega_{l00} \\ \\ \Omega_{l01} \\ \vdots \\ \\ \Omega_{l0(2^l-1)} \end{pmatrix} \quad l = 1, 2, \ldots, N_T \tag{3.43}$$

At the end of the tree phase, the "branch" of the hybrid tree, Ω_{N_T}, forms, which contains 2^{N_T} elements. The remainder of the group-based hybrid three is built based on the branch.

Equation (3.44) shows how the lattice-like phase is built. The number of groups increases one at every step in the lattice-like phase, but the group size is fixed, equal to 2^{N_T}. That is, Ω_l contains $l - N_T + 1$ groups (for $N_T < l \leq N_L$), and the mth group, Ω_{lm}, equals the "branch" of the hybrid tree, Ω_{N_T}, plus $(l - N_T - m)$ pieces of "leaves"

, $\overline{\omega}^{l}_{N_T}$, as illustrated in Equation (3.44).

$$\Omega_{lm} = \begin{pmatrix} \Omega_{lm0} \\ \Omega_{lm1} \\ \vdots \\ \Omega_{lm(2^{N_T}-1)} \end{pmatrix} = \Omega_{N_T} + (l - N_T - m)\overline{\omega}^{l}_{N_T}$$

$$l = N_T + 1, N_T + 2, \ldots, N_L; \qquad m = 0, 1, \ldots, l - N_T \tag{3.44}$$

The leaf at $t_{l'}$ is the average of ω^k (for $k = N_T + 1, \ldots, l$), as formulated in Equation (3.45).

$$\overline{\omega}^{l}_{N_T} = \frac{\sum_{k=N_T+1}^{l} \omega^k}{l - N_T} \tag{3.45}$$

The number of groups stops growing in the strip phase, and all the groups in the strip phase are identical to the groups at the last step of the lattice-like phase, as indicated in Equation (3.46).

$$\Omega_l = \Omega_{N_L} \qquad l = N_L + 1, N_L + 2, \ldots, N_D - 1 \tag{3.46}$$

Arrows connecting groups in the group-based hybrid tree are arrow topologies (indicated as "arrows"), each of which represents a group of regular arrows sharing similarities. "Arrows"are very different across phases, and they are interpreted in below:

1. the tree phase (i.e., $0 \leq l < N_T$)

   One "arrow"goes out from Ω_{l0} and points to $\Omega_{(l+1)0}$. It represents that a pair of regular arrows starts from every Ω_{l0n} ($\forall n \in N_l$), one towards $\Omega_{(l+1)0(2n)}$ with probability P_η and the other towards $\Omega_{(l+1)0(2n+1)}$ with probability $1 - P_\eta$.

2. the lattice-like phase (i.e., $N_T \leq l < N_L$)

   A pair of "arrows"goes out from Ω_{lm} ($\forall m \in M_l$). The first "arrow"starts from the first half elements of Ω_{lm}, and it goes towards $\Omega_{(l+1)m}$, the mth group at the subsequent step. This "arrow"represents that two regular arrows start from Ω_{lmn} (for $n = 0, 1, \ldots, 2^{N_T-1} - 1$), one towards $\Omega_{(l+1)m(2n)}$ with probability P_η and the other towards $\Omega_{(l+1)m(2n+1)}$ with probability $1 - P_\eta$. The other "arrow"starts from the remain half elements of Ω_{lm}, and it points to $\Omega_{(l+1)(m+1)}$, the $(m+1)$th group at the next step. It represents that two regular arrows start from Ω_{lmn} (for $n = 2^{N_T-1}, 2^{N_T-1}+1, \ldots, 2^{N_T} - 1$) , one towards $\Omega_{(l+1)(m+1)(2(n-2^{N_T-1}))}$ with probability P_η and the other towards $\Omega_{(l+1)(m+1)(2(n-2^{N_T-1})+1)}$ with probability $1 - P_\eta$.

3. the strip phase (i.e., $N_L \leq l < N_D$)

   - A pair of "arrows"goes out from Ω_{l0}, which is the same as the pairs in phase two.
   - A pair of "arrows"starts from $\Omega_{l(N_L-N_T)}$, which is almost the same as the pairs in phase three except that they are towards groups $N_L - N_T - 1$ and $N_L - N_T$, respectively.
   - Two pairs of "arrows"start from each of the remaining Ω_{lm}. One pair is the same as these in phase two except that the probability of jump is reduced by half. For the other pair of "arrows", one "arrow"connects the first half

elements of Ω_{lm} to the $\Omega_{(l+1)(m-1)}$, and the other "arrow"links the second half elements of Ω_{lm} to $\Omega_{(l+1)m}$. The probability of jump is also reduced by half.

A hybrid tree has $2^{N_T}\left(1+\frac{(N_L-N_T+1)(N_L-N_T)}{2}+(N_D-N_L)(N_L-N_T+1)\right)-1$ nodes. Thus, the computational complexity is about $O(2^{N_T}(N_D-N_T)(N_L-N_T))$. For example, the computational complexity is reduced about 96% if a seventeen-steps binomial tree is replaced by a seventeen-steps hybrid tree, which has six steps in the tree phase, four steps in the lattice-like phase, and seven steps in the strip phase. Therefore, replacing a binomial tree with a hybrid tree substantially improves the computational efficiency. Meanwhile, the hybrid tree will not severely impair the solution accuracy if it is properly designed.

3.6.3 Approximating D_t and η_t as A Multi-Layer Lattice

Before taking CTT, η_t, as an underlying process, decisions at t are based on two state variables, demand D_t and the available KW-capacity c_t. D_t is the only underlying process in such scenario, so a single lattice is capable of representing uncertainty over the PLC. After η_t is considered as one addition underlying process, it becomes the other state variable in the decision. A single lattice is insufficient for illustrating two underlying processes. Multi-layer lattice is a form of representing multiple underlying variables using lattices [Erickson (2000)]. One lattice/tree illustrates one underlying variable, and then all the lattices/trees are combined to form a multiple lattice. Since η_t and D_t could be discretely approximated by a hybrid tree and a binomial lattice, respectively, a multi-layer lattice is constructed to approximate the two underlying processes.

The between-layers variation represents the unpredictability in η_t and the within-layer variation identifies the unpredictability in D_t.

Figure 3.11 demonstrates an example wherein a binomial lattice (for approximating D_t) is embedded in a binomial tree (for approximating η_t), forming a multi-layer lattice. $\Delta T'$ is the time step of the binomial tree, and the time step of the binomial lattice is ΔT. $\Delta T'$ and ΔT are properly chosen such that $\frac{\Delta T'}{\Delta T}$ is a positive integer. η_{lmn}, a unique level of CTT at $t_{l'}$ ($\forall l \in L$), is associated with a segment of demand lattice D^l in Equation (3.47), forming a unique segment of the multi-layer lattice (η_{lmn}, D^l). This segment is in the length of $N_{LS} = \frac{\Delta T'}{\Delta T}$, beginning with lN_{LS} demand levels, increasing one level in every ΔT, and ending in $(l+1)N_{LS} - 1$ levels.

$$D^l = \left\{ D_{ij} \;\middle|\; \begin{array}{l} i \in I_l = \{lN_{LS}, lN_{LS}+1, \ldots, (l+1)N_{LS}-1;\} \\ \\ j \in J_i = \{0, 1, \ldots, i\} \end{array} \right\} \tag{3.47}$$

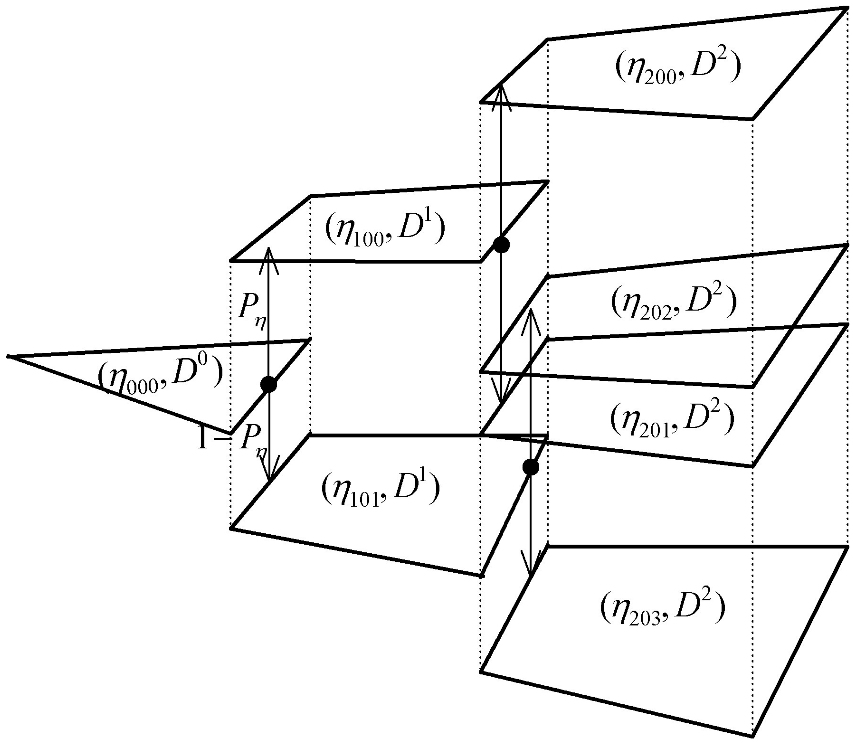
3.6.4 Optimization of KWA On A Multi-Layer Lattice

The optimization of KWA on two underlying processes is similar to the optimization on one underling process. After applying some modifications to the work in Section 3.5.4, the optimization of KWA w.r.t. D_t is extended to the optimization w.r.t. D_t and η_t. To make the discussion focused, here the length of PLC is assumed as known.

To articulate what the optimization on a multi-layer lattice is, the pseudo-code for the optimization procedures is provided in below.

1. Design of the Multi-layer Lattice for approximating η_t and D_t

   estimate the decision time horizon T_D;



each segment of the multi-layers lattice is identified as (η_{lmn}, D^l)

l **is the discrete time index of** η_t

m **is the bwteen-groups index of** η_t

n **is the within-group index of** η_t

$$D^l = \left\{ D_{ij} \middle| \begin{array}{l} i \in I_l = \{lN_{LS}, lN_{LS}+1, \cdots, (l+1)N_{LS}-1\} \\ j \in J_i = \{0, 1, \cdots, i\} \end{array} \right\}$$

i **is the discrete time index of** D_t

j **is the level index of** D_t

$N_{LS} = \frac{\Delta T'}{\Delta T}$ **is the length of lattice segment in unit of** ΔT

Fig. 3.11. A Multi-Layer Lattice Representing η_t and D_t

choose time step $\Delta T'$ and let $N_D = \left\lceil \frac{T_D}{\Delta T'} \right\rceil$;
denote $t_{l'}$ (for $l \in \{0, 1, \ldots, N_D - 1\}$) as the end of step l for η_t;
determine N_T, N_L and N_{LS}.

2. Backward DP procedure on the multi-layer lattice

for $l{:=}\ N_D - 1$ **to** 0

build demand lattice segment D^l using Equation (3.47);

backward DP procedure on $\left(\eta_{lmn}, D^l\right)$:

case1: $N_L \leq l < N_D$(the strip phase)
$\forall\ m \in \{0, 1, \ldots, N_L - N_T\}$, $n \in \left\{0, 1, \ldots, 2^{N_T} - 1\right\}$;

case2: $N_T \leq i < N_L$(the lattice-like phase)
$\forall\ m \in \{0, 1, \ldots, l - N_T\}$, $n \in \left\{0, 1, \ldots, 2^{N_T} - 1\right\}$;

case3: $0 \leq l < N_T$(tree phase)
$m = 0, \forall\ n \in \left\{0, 1, \ldots, 2^l - 1\right\}$.

endfor

The pseudo-code indicates that major procedures of the optimization are the design of the multi-layer lattice and the backward DP procedure which passes the strip phase, the lattice-like phase, and the tree phase in sequence.

Two things have to be determined in design of the multi-layer lattice. The first thing is to choose the step size in approximation of η_t. $\Delta T'$ should be chosen as small as possible so that Binomial process approximates Poisson process better. $P\left\{X_i = 2\right\} = \frac{e^{-\lambda_\eta \Delta T'}\left(\lambda_\eta \Delta T'\right)^2}{2!}$ can be taken as an criterion of choosing $\Delta T'$. $\Delta T'$ is chosen to make $P\left\{X_i = 2\right\}$ small enough so that the possibility of jumping twice or more can be ignored. The other thing is to determine N_T and N_L. After $\Delta T'$ is determined, sequence $S_{N_D - 1}(\omega) = \left\{\omega, \omega^2, \ldots, \omega^{N_D - 1}\right\}$ for constructing the hybrid tree is determined. An empirical method for determining N_T is to examine the standardized decrease in $S_{N_D-1}(\omega)$, as formulated in Equation (3.48).

$$\Delta\omega^l = \frac{\omega^l - \omega^{l+1}}{\omega - \omega^{N_D-1}} \tag{3.48}$$

N_T is chosen as where Equation (3.48) falls below a critical value δ_T (e.g., 5%). The choice of N_T identifies that remaining elements after ω^{N_T} in the sequence just have a trivial change. N_L is determined empirically too. Equation (3.49) calculates the percentage of remaining elements in $S_{N_D-1}(\omega)$ after ω^l.

$$\omega^l_{tail} = \frac{\sum_{k=l+1}^{N_D-1} \omega^k}{\sum_{k=1}^{N_D-1} \omega^k} \tag{3.49}$$

N_L is chosen as where the remaining elements in $S_{N_D-1}(\omega)$ account for less than δ_L amount of all the elements in the sequence.(e.g., $\delta_L = 5\%$). N_L identifies that elements after ω^{N_L} is very small, and they can be taken as zeros.

The valuation function at t_i $(i \in I_l)$ is in Equation (3.50). It has three state variables D_i, c_i and η_l, which are demand, the KW-capacity, and CTT at then respectively. Decisions to make are the KW-capacity for the subsequent step c_{i+1} and the current production scale x_{wi}.

$$\begin{aligned}
V\left(c_{i+1},\ x_{wi}|D_i, c_i, \eta_l\right) = V\left(c_{i+1}, g^Z(c_{i+1})|D_i, c_i, \eta_l\right) \\
= p_{t_i} \min\left(D_i, N_{IC} g^Z(c_{i+1}) y\left(c_{i+1}, g^Z(c_{i+1})|c_i, \eta_l\right)\right) \\
- c_v g^Z(c_{i+1}) - C^{IP}(c_{i+1}|c_i) - C^{IT}(c_{i+1}|c_i) - C^{CT}(c_{i+1}|c_i) \\
- EV\left(D_i, c_{i+1}, \eta_l^{x_\eta}\right)
\end{aligned} \tag{3.50}$$

$$\eta_l := \eta_{lmn} \quad \exists l \in L, \forall m \in M_l, \forall n \in N_l; \quad D_i := \forall D_{ij} \in D^l; \quad c_i := \forall c \in C$$

The corresponding optimal valuation function is in Equation(3.51).

$$\begin{aligned}
V^*\left(D_i, c_i,\ \eta_l\right) = \max_{c_{i+1} \in C} \left\{V\left(c_{i+1}, g^Z(c_{i+1})|D_i, c_i, \eta_l\right)\right\} \\
= p_{t_i} \min\left(D_i, N_{IC} g^Z(c^*_{i+1}) y\left(c^*_{i+1}, g^Z(c^*_{i+1})|c_i, \eta_l\right)\right) \\
- c_v g^Z(c^*_{i+1}) - C^{IP}(c^*_{i+1}|c_i) - C^{IT}(c^*_{i+1}|c_i) - C^{CT}(c^*_{i+1}|c_i) \\
+ EV\left(D_i, c^*_{i+1}, \eta_l^{x_\eta}\right)
\end{aligned} \tag{3.51}$$

$$\eta_l := \eta_{lmn} \quad \exists l \in L, \forall m \in M_l, \forall n \in N_l; \quad D_i := \forall D_{ij} \in D^l; \quad c_i := \forall c \in C$$

η_{lmn} on the hybrid-tree are classified as different categories according to where it may go. Thus, a parameter x_η is added to the state variable η_l for identifying what category a value of η_l belongs to, as shown in Equations (3.50) and (3.51). Evaluation of $EV(D_i, c_{i+1}, \eta_l^{x_\eta})$ thereby is complicated. Table 3.2 lists formulates of $EV(D_i, c_{i+1}, \eta_l^{x_\eta})$ at any value of x_η.

Table 3.2.
Expected Maximum Future Value on The Multi-Layer Lattice

x_η	$\eta_l := \eta_{lmn} \quad \exists l \in L^{x_\eta}, \forall m \in M_l^{x_\eta}, \forall n \in N_l^{x_\eta}$			$EV(D_i, c_i, \eta_l^{x_\eta})$
	L^{x_η}	$M_l^{x_\eta}$	$N_l^{x_\eta}$	
0	$l = N_D$	$0 \leq m \leq N_L - N_T$	$0 \leq n < 2^{N_T}$	0
1	$N_L \leq l < N_D$	$m = 0$	$0 \leq n < 2^{N_T - 1}$	Equation (3.52)
2			$2^{N_T - 1} \leq n < 2^{N_T}$	Equation (3.53)
3		$m = N_L - N_T$	$0 \leq n < 2^{N_T - 1}$	Equation (3.54)
4			$2^{N_T - 1} \leq n < 2^{N_T}$	Equation (3.55)
5		$0 < m < N_L - N_T$	$0 \leq n < 2^{N_T - 1}$	$0.5EV(D_i, c_i, \eta_l^1)$ + $0.5EV(D_i, c_i, \eta_l^3)$
6			$2^{N_T - 1} \leq n < 2^{N_T}$	$0.5EV(D_i, c_i, \eta_l^2)$ + $0.5EV(D_i, c_i, \eta_l^4)$
7	$N_T \leq l < N_L$	$0 \leq m = l - N_T$	$0 \leq n < 2^{N_T - 1}$	$EV(D_i, c_i, \eta_l^1)$
8			$2^{N_T - 1} \leq n < 2^{N_T}$	$EV(D_i, c_i, \eta_l^2)$
9	$0 \leq l < N_T$	$m = 0$	$0 \leq n < 2^l$	$EV(D_i, c_i, \eta_l^1)$
10	remains			Equation (3.56)

$$
\begin{aligned}
EV\left(D_i, c_{i+1}, \eta_l^1\right) = e^{-r_f \Delta T'} \Big[& P_\eta P_{rn} V^*\left(u_i D_i, c_{i+1}, \eta_l^{u1}\right) \\
& + P_\eta (1 - p_{rn}) V^*\left(d_i D_i, c_{i+1}, \eta_l^{u1}\right) \\
& + (1 - P_\eta) P_{rn} V^*\left(u_i D_i, c_{i+1}, \eta_l^{d1}\right) \\
& + (1 - P_\eta)(1 - P_{rn}) V^*\left(d_i D_i, c_{i+1}, \eta_l^{d1}\right) \Big]
\end{aligned} \tag{3.52}
$$

$$\eta_l^1 := \eta_{lmn} \quad \exists l \in L^1, \forall m \in M_l^1, \forall n \in N_l^1;$$

$$\eta_l^{u1} = \eta_{(l+1)m(2n)}; \quad \eta_l^{d1} = \eta_{(l+1)m(2n+1)};$$

$$D_i := \forall D_{\left(\left\lfloor \frac{T_D}{\Delta T} \right\rfloor - 1\right) j} \in D^l; \quad c_{i+1} := \forall c \in C.$$

$$\begin{aligned}EV\left(D_i,c_{i+1},\eta_l^2\right) = e^{-r_f\Delta T'}\big[&P_\eta P_{rn}V^*\left(u_iD_i,c_{i+1},\eta_l^{u2}\right)\\
&+P_\eta(1-p_{rn})V^*\left(d_iD_i,c_{i+1},\eta_l^{u2}\right)\\
&+(1-P_\eta)P_{rn}V^*\left(u_iD_i,c_{i+1},\eta_l^{d2}\right)\\
&+(1-P_\eta)(1-P_{rn})V^*\left(d_iD_i,c_{i+1},\eta_l^{d2}\right)\big]\end{aligned} \tag{3.53}$$

$\eta_l^2 := \eta_{lmn} \quad \exists l \in L^2, \forall m \in M_l^2, \forall n \in N_l^2;$

$\eta_l^{u2} = \eta_{(l+1)(m+1)(2(n-2^{N_T-1}))}; \quad \eta_l^{d2} = \eta_{(l+1)(m+1)(2(n-2^{N_T-1})+1)};$

$D_i := \forall D_{((l+1)N_{LS}-1)j} \in D^l; \quad c_{i+1} := \forall c \in C.$

$$\begin{aligned}EV\left(D_j,c_{j+1},\eta_l^3\right) = e^{-r_f\Delta T'}\big[&P_\eta P_{rn}V^*\left(u_iD_i,c_{i+1},\eta_i^{u3}\right)\\
&+P_\eta(1-p_{rn})V^*\left(d_iD_i,c_{i+1},\eta_i^{u3}\right)\\
&+(1-P_\eta)P_{rn}V^*\left(u_iD_i,c_{i+1},\eta_i^{d3}\right)\\
&+(1-P_\eta)(1-P_{rn})V^*\left(d_iD_i,c_{i+1},\eta_i^{d3}\right)\big]\end{aligned} \tag{3.54}$$

$\eta_l^3 := \eta_{lmn} \quad \exists l \in L^3, \forall m \in M_l^3, \forall n \in N_l^3;$

$\eta_l^{u3} = \eta_{(l+1)(m-1)(2n)}; \quad \eta_l^{d3} = \eta_{(l+1)(m-1)(2n+1)};$

$D_i := \forall D_{((l+1)N_{LS}-1)j} \in D^l; \quad c_{i+1} := \forall c \in C.$

$$\begin{aligned}EV\left(D_i,c_{i+1},\eta_l^4\right) = e^{-r_f\Delta T_\eta}\big[&P_\eta P_{rn}V^*\left(u_iD_i,c_{i+1},\eta_l^{u4}\right)\\
&+P_\eta(1-p_{rn})V^*\left(d_iD_i,c_{i+1},\eta_l^{u4}\right)\\
&+(1-P_\eta)P_{rn}V^*\left(u_iD_i,c_{i+1},\eta_l^{d4}\right)\\
&+(1-P_\eta)(1-P_{rn})V^*\left(d_iD_i,c_{i+1},\eta_l^{d4}\right)\big]\end{aligned} \tag{3.55}$$

$\eta_l^4 := \eta_{lmn} \quad \exists l \in L^4, \forall m \in M_l^4, \forall n \in N_l^4;$

$\eta_l^{u4} = \eta_{(l+1)m(2(n-2^{N_T-1}))}; \quad \eta_l^{d4} = \eta_{(l+1)m(2(n-2^{N_T-1})+1)};$

$D_i := \forall D_{((l+1)N_{LS}-1)j} \in D^l; \quad c_{i+1} := \forall c \in C.$

$$
\begin{aligned}
EV\left(D_i, c_{i+1}, \eta_l^{10}\right) &= e^{-r_f \Delta T'}\left[P_{rn} V^*\left(u_i D_i, c_{i+1}, \eta_l^{10}\right)\right. \\
&\left. \qquad +(1-P_{rn}) V^*\left(d_i D_j, c_{i+1}, \eta_l^{10}\right)\right] \\
\eta_l^{10} &:= \eta_{lmn} \quad \exists l \in L^{10}, \forall m \in M_l^{10}, \forall n \in N_l^{10}; \\
D_i &:= \forall D_{ij} \in D^l, i \neq (l+1) N_{LS} - 1; \quad c_{i+1} := \forall c \in C.
\end{aligned}
\tag{3.56}
$$

Major changes in extending the optimization of KWA with one underlying process (D_t) to the optimization with two underlying processes (D_t and η_t) are summarized in below:

- the number of state variables in the yield function is changed from one to two: c_t and η_t;
- the number of state variables in the valuation function is changed from two to three: D_t, c_t, and η_t;
- the number of loops in the backward DP procedure is changed from one to two: one for η_t and one for D_t;
- a single-layer lattice is replaced by a multi-layer lattice; and
- because of using the hybrid tree to approximate η_t, the expected future value has a variety of formulations, according to what category the value of state variable η_t belongs to.

The problem this section is not the most general case. However, The work in this section will not change significantly if assumptions in this section are relaxed, which indicates that major research work have been developed in this section. For instance, after relaxing the assumption that T_m is known, the optimization scheme becomes repeated

DP procedures on a family of multi-layer lattices. If σ_η is not equal to zero, the DP procedure is still conducted on a multi-layer lattice. However, the number of layers increases. Providing sufficient computing resources and techniques, the abovementioned generalizations of this section are solvable.

Chapter 4

Results of Research

Chapter 3 presented the model for attaining knowledge workforce agility (**KWA**) during the product life cycle (**PLC**) using real options (**RO**). KWA is modeled as American-type options. Thus, the optimization must be obtained numerically. No general conclusion can be reached on any single numerical example. Thus, to bring the completion of the research objectives of this thesis, this chapter assesses the significance of the work through mathematical examination, study designs and detailed results analyses.

4.1 System Settings and Study Overview

A simulated system of producing a new generation of DRAM product is set up to facilitate obtaining necessary results of the research. In the simulated system, a series of studies are designed to accomplish the results analyses and discussions.

4.1.1 System Settings

The simulated system is set up through parameterization. Major parameters and corresponding values are listed in Table 4.1. These parameter values are chosen based either on extensive literatures or on approximate reasoning to insure the numerical demonstration sufficiently representative.

Table 4.1.
List of Parameter Values in the Numerical Demonstration

Parameters	**Values**
the mean of T_m (μ_{T_m})	5years
the standard deviation of T_m (σ_{T_m})	1year
the time interval for discretized demand (ΔT)	$\frac{1}{12}$year
the initial demand (D_0)	0.5Munits/month
the demand volatility (σ)	0.2
the expected market size (M)	3000M units
the initial value of η_t (η_0)	25%
the equilibrium value of η_t (η_m)	25%
the jump size of η_t (r_η)	50%
the jump intensity of η_t (λ_η)	0.5/year
the reverting speed after jump (α_η)	$\log 2$/year
the initial sales price (p_0)	\$150
the speed of price erosion (λ_p)	0.25/year
the discounted rate (r)	12%/year
the risk-free rate (r_f)	8%/year
the price of market risk (λ)	10%
the fixed cost(F)	\$3.843B
the production variable cost (c_v)	\$2.8K/wafer
the startup cost for initial training (IT) (a_0^{IT})	\$50K
the marginal cost for IT ($a_1^{IT} + xa_2^{IT}$)	$(3875K + 500Kx)$/team
the startup cost for continuous training (CT)(a_0^{CT})	\$10K
the marginal cost for CT ($a_1^{CT} + xa_2^{CT}$)	$(4000K + 200Kx)$/team
the ratio of production loss in IT (a_{it}^{IP})	$13.9e^{-0.25t}M$
the speed of production loss in IT (a_{2t}^{IP})	$0.225e^{-2.3t+0.18t^2}M$
the number of chips resided in one wafer(N_{IC})	140
the rate of yield improvement (λ_y)	23026wafers/team
the maximum production scale (W)	700Kwafer starts/month
the maximum knowledge workforce capacity (C)	100teams

T_m, the time of demand maturity, is normal distributed, with a mean of five years and a standard deviation of one year in this generation. The value of μ_{T_m} and σ_{T_m} are adopted from the work by Bollen (1999). Demand comes at the beginning of each month, and it is 0.5 million in the first month during the PLC. Demand exhibits stochastic behavior during the PLC, with a demand volatility of 0.2. The expected cumulative demand of this generation is 3 billion. The estimates of D_0, M, and σ are based on the knowledge obtained in fitting the demand model.

The initial value of η_t is 25%, and it is equal to the equilibrium value. Jumps of η_t happen like a Poisson process during the PLC. η_t jumps once in every two years, on average, and the jump size is 50%. η_t decreases gradually after jumps, at a speed of $\ln 2$ per year, that is, it decreases by half in every one year. Without real values to refer to, thesis thesis makes reasonable assumptions about it, and uses sensitivity ananlyses to reduce the bias caused by making assumptions.

The sales price is \$150 at the beginning of the PLC, which decreases exponentially during the PLC at a speed of 0.25 per year. The demand model is estimated based on literatures such as Mody & Wheeler (1987) and Siebert (2003). The discounted rate of cash flow of 12%, the risk-free rate is 8%, and the price of market risk is 10%, which are all commonly used in extensive interatures.

The fixed production cost is \$3.843B, which includes the cost of building the plant and buying equipments, and ten-years labor cost. The variable cost averaged on each wafer is \$2.8K, which is composed of the material cost and the operation cost. These values are based on the knowledge about semiconductor manufacturing. The cost for starting up an initial training is \$50K, and the marginal cost for training the xth team is $\$(3875K + 500Kx)$. The cost for starting a continuous training is $\$10K$, and the marginal cost for the xth team is $\$(4000K + 200Kx)$. The estimation of the production loss uses parameters of the previous generation, the values of which are assumed to be the same as in the new generation. In addition, the steady state yield of the previous generation is 90%. Without real data, these values are assumed based on reasonable reasoning from other type of costs and benefits.

How many chips can be put on a wafer is determined by the wafer size and fabrication techniques. The number could be very different, from tens to thousands. This thesis assumes 140 chips reside on one wafer in this generation, and the number of chips out of them can pass the final test is represented by yield. The rate of yield improvement is 23026 wafer starts per team, meaning that a 90% can be reached if on average every 10k wafers are supervised by one team. The maximum production scale is $700K$ wafer starts per month, and this generation can at maximum have 100 teams for solving problems in the wafer fabrication. The values are assumed based on our knowledge about semiconductor manufacturing.

Although this thsis has difficulty in obtaining a whole and systematic set of data, the limited data in above and assumptions this thesis has made still can paritally support the numerical demonstration of reseach results.

4.1.2 Overview of Studies for Assessing The Importance of Research

To obtain well-rounded conclusions about the work of this thesis, the analyses and discussion of the research results are formed by four studies described below:

1. articulating benefits of KWA in general PLC environments by way of analytically examining the underlying stochastic processes with respect to the parameter space,

2. assessing the RO approach for attaining KWA through a comprehensive comparison of it to the other two representative agility-driven approaches under demand uncertainty,

3. evaluating the expected profit growth that is generated by RO-based KWA from various sources of uncertainty, and

4. examining the numerical methods that are designed for reducing the computational complexity.

Whether the KWA has potential for improving business operations in PLC environments is explored in study 1. Study 2 further investigates if modeling KWA as RO and optimizing KWA using the RO valuation techniques are the approach for using KWA rationally and wisely. Study 3 subsequently defines and measures the financial reward from adoption of RO-based KWA. The reliability of results is examined by study 4.

4.2 An Analytical Examination of The PLC Environment

An analytical examination of the underlying process models w.r.t. the parameter space informs us what benefits that KWA has in more general PLC environments.

4.2.1 Benefits of KWA under Demand Uncertainty

The demand model in Equation (3.1) has four parameters: σ, T_m, D_0 and M, each of which represents one important characteristic of demand. σ is the demand volatility which measures the scale of stochasticity in demand. T_m is the time of the demand maturity, which is approximately the middle of the PLC and thus informs us the length of PLC. D_0 is the initial demand, so it represents the initial adoption level of product. M is the expected cumulative demand over the PLC, which measures the expected market size. The percent change in demand over the change in any abovementioned parameter, which is denoted as $\%\Delta D_t(\cdot)$ (for distinguishing from the relative change of demand over time $\frac{\Delta D_t}{D_t}$), informs us how on the generalized PLC environment.

Variation of D_t w.r.t. Change in σ

$\%\Delta D_t(\sigma)$, the percent change in D_t w.r.t. σ at t ($t \in [0, T]$), is given in Equation (4.1) according to Appendix J.

$$\%\Delta D_t(\sigma) = e^{-\frac{1}{2}\sigma^2 t\left(2\frac{\Delta\sigma}{\sigma}+1\right)+\sigma W_t\left(\frac{\Delta\sigma}{\sigma}\right)} - 1 \tag{4.1}$$

To display how the demand distribution is varied with the growth in demand volatility, the 99.6% range of $\%\Delta D_t(\sigma)$ over the PLC is illustrated at two levels of increase in σ: 50% (the gridded area) and 100% (the striped area), as in Figure 4.1. Two things are observed in Figure 4.1:

- an increase in the demand volatility is accompanied by an expansion in the demand distribution, which is further widened over time yet at a reduced speed; and
- the demand distribution will extend further if the demand volatility remains growing, which is especially clear on the upper side of the distribution.

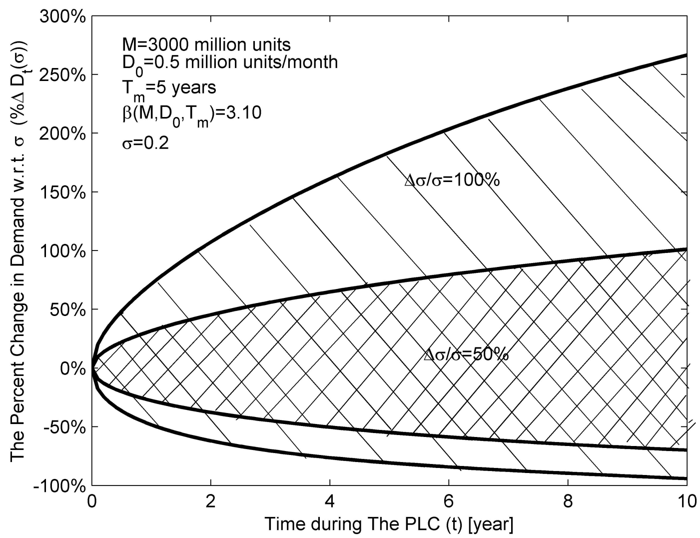


Fig. 4.1. The Percent Change in D_t w.r.t. σ during The PLC

The observations indicate that the growth in demand volatility intensifies the desire for KWA. Manufacturers who use KWA in highly volatile PLC environments are capable of catching opportunities derived from the high demand and of reducing risks from holding an access knowledge workforce when demand drops substantially.

Variation of D_t w.r.t. Change in T_m

The ith partial derivative of D_t w.r.t. T_m is estimated by Equation (J.17) in Appendix J. Thus, the percent change in D_t w.r.t. T_m at any time t during the PLC, $\%\Delta D_t\left(T_m\right)$, can be obtained using a Taylor expansion, as in Equation (4.2).

$$\%\Delta D_t\left(T_m\right) = \sum_{i=1}^{\infty} \frac{\left(\frac{\Delta T_m}{T_m}\right)^i}{i!} \prod_{j=0}^{i-1} \left(\frac{\beta^2}{\beta^2-1}\frac{t}{T_m}\left(\beta^2\left(\frac{t}{T_m}-1\right)-1\right)-j\right) \tag{4.2}$$

To show how the shrink of PLC length changes the future demand, $\%\Delta D_t\,(T_m)$ at three levels of decrease in T_m: -1%, -10% and -25%, and at any time during the PLC are illustrated in Figure 4.2. The figure shows that:

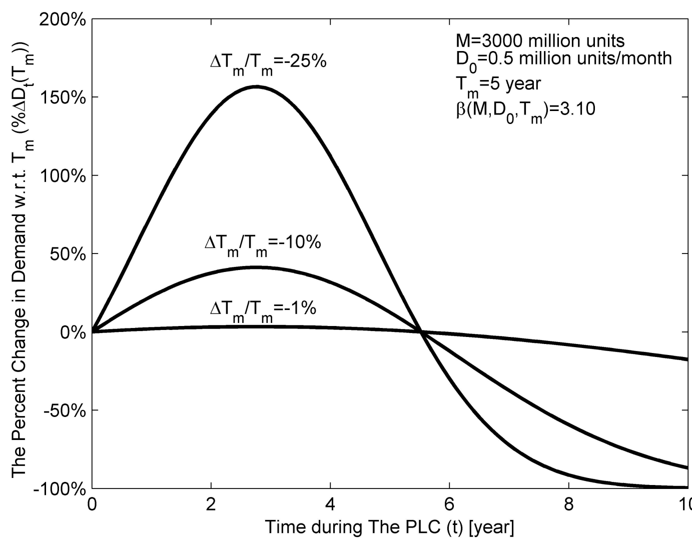


Fig. 4.2. The Percent Change in D_t w.r.t. T_m during The PLC

- the shrink of PLC length is associated with the demand increase in early in the PLC and with demand decrease later;
- a shorter PLC is accompanied by a larger change in demand, which is heterogeneous over time.

The observations indicate that a shorter PLC places pressures on manufacturers since it pushes a great amount of demand shifting to the early PLC. However, KWA turns the pressures into opportunities for earning more profits because the sales price is also high in the early PLC. Therefore, manufacturers benefit from KWA in short PLCs, and the effect is more clear when the PLC becomes shorter.

Variation of D_t w.r.t. Change in D_0

The ith partial derivative of D_t w.r.t. D_0 is calculated by Equation (J.16) in Appendix J. Thus, the percent change in D_t w.r.t. D_0 at any time t during the PLC, $\%\Delta D_t\left(D_0\right)$, can be evaluated using a Taylor expansion, as in Equation (4.3).

$$\%\Delta D_t\left(D_0\right) = \sum_{i=1}^{\infty} \frac{\left(\frac{\Delta D_0}{D_0}\right)^i}{i!} \prod_{j=0}^{i-1} \left(\frac{\beta^2}{1-\beta^2}\left(2+\frac{t}{T_m}\left(2-\frac{t}{T_m}\right)\right)-j\right) \tag{4.3}$$

It is well known that pursuing a high initial adoption level is important, and yet is expensive. To observe how the decrease of the initial adoption level changes the future demand, $\%\Delta D_t\left(D_0\right)$ at three levels of decrease in D_0: -1%, -10% and -25%, and at any time during the PLC are illustrated in Figure 4.3. The figure suggests the following:

- a drop of the initial adoption level causes an increase in demand,
- demand near the middle of the PLC is the most sensitive to the drop of the initial adoption level while the least at either end, and
- demand will grow quickly if the initial adoption level keeps decreasing.

The observations indicate that pursuing a high initial adoption level may hurt demand growth in the remainder of the PLC. A high initial adoption level is not a necessity since manufacturers who use KWA can easily satisfy the demand growth although the growth is very different over the PLC.

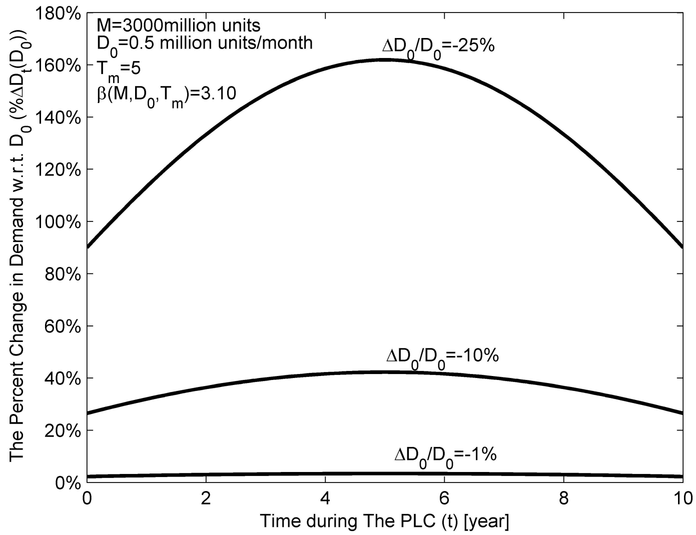


Fig. 4.3. The Percent Change in D_t w.r.t. D_0 during The PLC

Variation of D_t w.r.t. Change in M

The partial derivative of D_t w.r.t. M is attained in Equation (J.15) of Appendix J. Thus, the percent change in D_t w.r.t. M at any time t during the PLC, $\%\Delta D_t\,(M)$, can be obtained using a Taylor expansion, as in Equation (4.4).

$$\%\Delta D_t\,(M) = \sum_{i=1}^{\infty} \frac{\left(\frac{\Delta M}{M}\right)^i}{i!} \prod_{j=0}^{i-1} \left(\frac{\beta^2}{\beta^2 - 1} \frac{t}{T_m} \left(2 - \frac{t}{T_m}\right) - j \right) \tag{4.4}$$

To find how the growth of the expected market size changes the layout of future demand, $\%\Delta D_t\,(M)$ at any time during the PLC and at three levels of increase in M: 1%, 10% and 25%, are illustrated in Figure 4.4. The figure indicates that:

- the growth of the market size leads to a demand increase throughout the PLC,

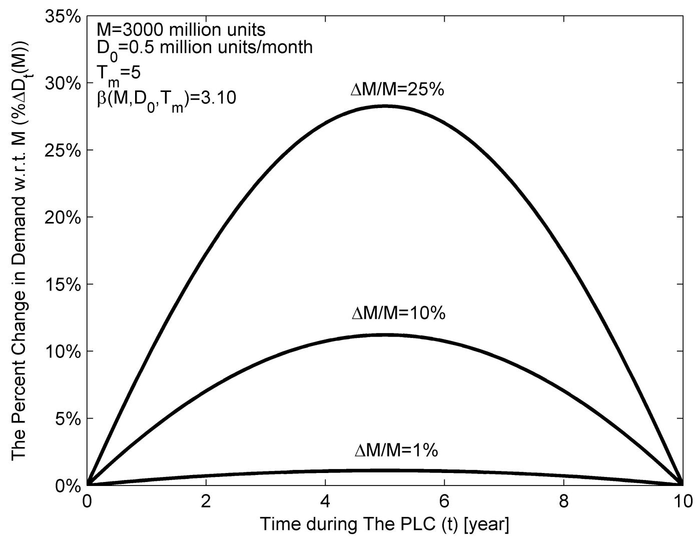


Fig. 4.4. The Percent Change in D_t w.r.t. M during The PLC

- demand in the middle of the PLC is the most sensitive to the growth of the market size while the least at either end, and
- the pace of demand increase is relatively stable when the market size is growing.

The observations inform us that manufacturers with KWA feel no difficulty to meet the varying demand increase over the PLC, which is caused by the growth of the expected market size.

After examining the demand model with respect to the parameter space over the PLC, KWA is shown to have potential for releasing pressures on manufacturers in pursuing the interests associated with the unstable and volatile demand during the PLC. The pressures are often from volatile demand, from shorting the PLC, from low initial product adoption levels, or from the growth of market size. With KWA, manufacturers are capable of reaching desired levels of knowledge workforce (**KW**) capacity to accommodate changes in demand.

4.2.2 Benefits of KWA in KW Dynamics

The large and sudden increases in the percent of labor time spent on the continuous training (**CTT**), η_t, caused by adoption of production technology advances is characterized by the parameters r_η, λ_η and α_η in the CTT model. The jump size, r_η, calibrates the scale of the stochastic CTT jumps, The jump intensity, λ_η, measures the frequency of the stochastic CTT jumps during the PLC, and the reverting speed after jumps, α_η, represents the learning capability of the knowledge workforce. The distribution of η over the PLC may vary as the parameters change. The percent change in $VAR\left[\eta_t\right]$ with respect to any abovementioned parameter, which is denoted as $\%\Delta VAR_{(\cdot)}\left[\eta_t\right]$, will give insight into the CTT jumps. $\%\Delta VAR_{(\cdot)}\left[\eta_t\right]$ is obtained by directly taking the difference between the $VAR\left[\eta_t\right]$ value before and after the parameter changes.

Variation of η_t w.r.t. Change in r_η

$\%\Delta VAR_{r_\eta}[\eta_t]$ is the percent change in the variance of η_t w.r.t. the jump size r_η, and the expression of $\%\Delta VAR_{r_\eta}[\eta_t]$ is obtained in Equation (4.5).

$$\%\Delta VAR_{r_\eta}\left[\eta_t\right] = \frac{1}{1+\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}}\left[\left(\frac{\Delta r_\eta}{r_\eta}+1\right)^2-1\right] \tag{4.5}$$

Equation (4.5) shows that $\%\Delta VAR_{r_\eta}[\eta_t]$ is a nondecreasing quadratic function of the percent change in r_η. The relation is homogeneous over the PLC, and yet is heterogeneous over $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$ which is a ratio manifesting the weight of the two sources of uncertainty in η_t: the mean-reverting diffusion process and the Poisson jumping process. $\sigma_\eta^2 \gg \lambda_\eta r_\eta^2$ indicates that the mean-reverting process is the major source of uncertainty in η_t. $\sigma_\eta^2 \ll \lambda_\eta r_\eta^2$ represents the scenario that the Poisson jumping process dominates in the sources of uncertainty. Thus, analyses in this section use $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$ to calibrate the significance of the jump effect.

To show how the change of r_η impacts the η_t distribution at different values of $\frac{\sigma_\eta}{\lambda_\eta r_\eta^2}$, the percent change in variance of η_t, $\%\Delta VAR_{r_\eta}[\eta_t]$, over a range of $\frac{\Delta r_\eta}{r_\eta}$, [-100%, 100%], is illustrated in Figure 4.5. The shaded area in Figure 4.5 is the feasible region

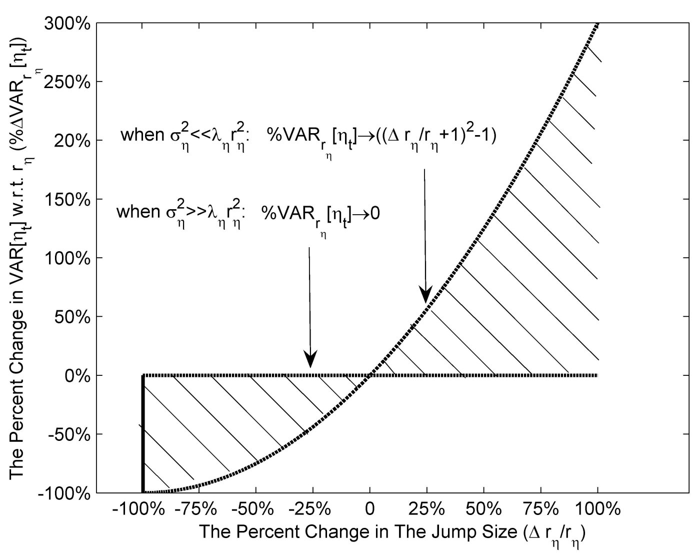


Fig. 4.5. The Percent Change in $VAR[\eta_t]$ w.r.t. r_η

of $\%\Delta VAR_{r_\eta}[\eta_t]$ over the range of $\frac{\Delta r_\eta}{r_\eta}$, and the dashed lines identify the boundaries of the feasible region. Figure 4.5 shows that:

- $\%\Delta VAR_{r_\eta}[\eta_t]$ approaches $(\frac{\Delta r_\eta}{r_\eta}+1)^2-1$ as $\sigma_\eta^2 \ll \lambda_\eta r_\eta^2$, approaches 0 as $\sigma_\eta^2 \gg \lambda_\eta r_\eta^2$, and passes the point (0,0) in the figure for any value of $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$.
- $VAR[\eta_t]$ will become more sensitive to the change in r_η when $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$ decreases.

The observations indicates that, if the stochastic jumps dominate in the sources of uncertainty in η_t, the η_t distribution would clearly expand at an increasing pace when the jump size increases. Therefore, KWA benefits manufacturers in that it provides them with the desired range of knowledge workforce (**KW**) capacity, which is expected to be wide when a large jump size r_η leads to a strong jump effect.

Variation of η_t w.r.t. Change in λ_η

$\%\Delta VAR_{\lambda_\eta}[\eta_t]$ is the percent change in the variance of η_t w.r.t. the jump intensity, λ_η. Equation (4.6) is the expression of $\%\Delta VAR_{\lambda_\eta}[\eta_t]$.

$$\%\Delta VAR_{\lambda_\eta}[\eta_t] = \frac{1}{1+\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}} \frac{\Delta\lambda_\eta}{\lambda_\eta} \tag{4.6}$$

Equation (4.6) indicates that $\%\Delta VAR_{\lambda_\eta}[\eta_t]$ is a nondecreasing linear function of the relative change in λ_η. The relation is homogeneous over the PLC, and yet is heterogeneous over the ratio $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$.

To find how the change of λ_η affects the η_t distribution at different values of $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$, the percent change in variance, $\%\Delta VAR_{\lambda_\eta}[\eta_t]$, over a range of $\frac{\Delta\lambda_\eta}{\lambda_\eta}$, [-100%, 100%], is illustrated in Figure 4.6. The shaded area in Figure 4.5 is the feasible region of

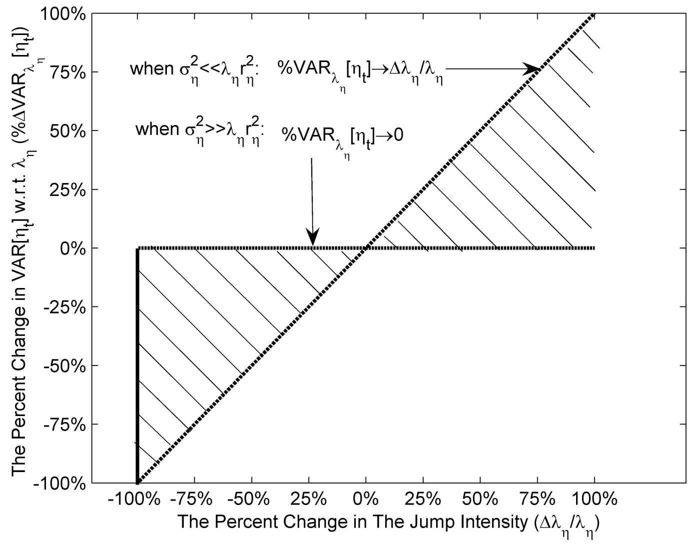


Fig. 4.6. The Percent Change in $VAR[\eta_t]$ w.r.t. λ_η

$\%\Delta VAR_{\lambda_\eta}[\eta_t]$ over the range of $\frac{\Delta\lambda_\eta}{\lambda_\eta}$, and the dashed lines identify the boundaries of the feasible region. Figure 4.6 suggests the following observations.

- $\%\Delta VAR_{r_\eta}[\eta_t]$ approaches $\frac{\Delta\lambda_\eta}{\lambda_\eta}$ as $\sigma_\eta^2 \ll \lambda_\eta r_\eta^2$, approaches 0 as $\sigma_\eta^2 \gg \lambda_\eta r_\eta^2$, and passes the point (0,0) in the figure for any value of $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$.

- $VAR[\eta_t]$ will become more sensitive to the change in λ_η when the ratio $\frac{\sigma_\eta^2}{\lambda_\eta r_\eta^2}$ decreases

The observations indicates that, if the stochastic jumps dominate in the sources of uncertainty in η_t, the η_t distribution would clearly expand at a constant rate when the jump intensity increases. Thus, KWA benefits manufacturers in that it provides them with the desired range of KW-capacity, which is expected to be wide when a large jump intensity λ_η leads to a strong jump effect.

Variation of η_t w.r.t. Change in α_η

$\%\Delta VAR_{\alpha_\eta}[\eta_t]$ is the percent change in $VAR[\eta_t]$ w.r.t. α_η, which is obtained in Equation (4.7).

$$\%\Delta VAR_{\alpha_\eta}[\eta_t] = -\frac{\frac{\Delta\alpha_\eta}{\alpha_\eta}}{1+\frac{\Delta\alpha_\eta}{\alpha_\eta}} + \frac{e^{-2\alpha_\eta t}\left(1-e^{-2\Delta\alpha_\eta t}\right)}{\left(1-e^{-2\alpha_\eta t}\right)\left(1+\frac{\Delta\alpha_\eta}{\alpha_\eta}\right)} \tag{4.7}$$

Equation (4.7) indicates that $\%\Delta VAR_{\alpha_\eta}[\eta_t]$ is changing during the PLC.

To observe the change of the η distribution w.r.t. α_η during the PLC, $\%\Delta VAR_{\alpha_\eta}[\eta_t]$ over a ten-years time horizon, [0,10], is illustrated in Figure 4.7. The shaded area in Figure 4.7 is the feasible region of $\%\Delta VAR_{\alpha_\eta}[\eta_t]$, and the boundaries of the feasible region are identified by the dashed lines. Besides the feasible region and the boundaries, Figure 4.7 further illustrates $\%\Delta VAR_{\alpha_\eta}[\eta_t]$ at two values of $\frac{\Delta\alpha_\eta}{\alpha_\eta}$: 50% and -50%, which are indicated by solid lines.

Figure 4.7 shows that:

- The η_t distribution expands when α_η decreases, and the expansion grows over the PLC at a reduced rate.
- The more α_η decreases, the quicker the η_t distribution is widened.
- When the maximum decrease of α_η reaches(i.e., $\frac{\Delta\alpha}{\alpha} = -100\%$), $\%\Delta VAR_{\alpha_\eta}[\eta_t]$ is bounded by $\frac{2\alpha_\eta t}{1-e^{-2\alpha_\eta t}} - 1$.

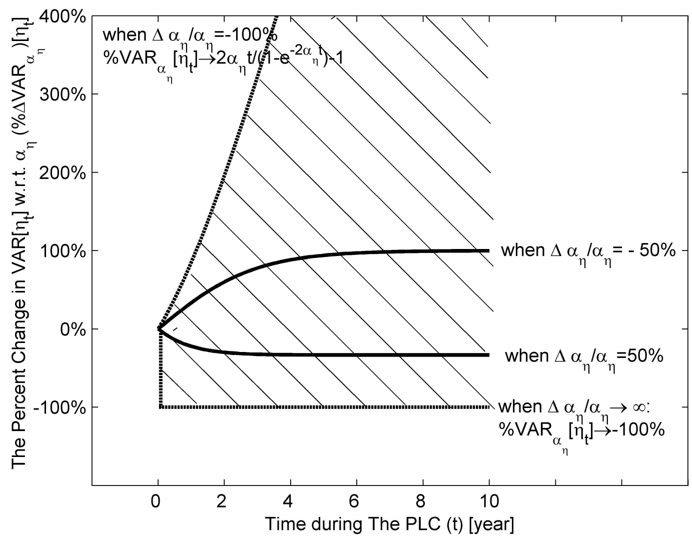


Fig. 4.7. The Percent Change in $VAR[\eta_t]$ w.r.t. α_η during The PLC

The observations indicate that the adoption of production technology advances during the PLC will substantially widen the η_t distribution progressively over time if the learning capability of the workforce is insufficient. The η_t distribution can quickly become extremely wide if the learning capability is drastically reduced. KWA can partly reduce the pressure of the insufficient learning capability, and it fulfills this mission by providing a wide range of KW-capacity to compensate for the highly unstable performance of the knowledge workforce in PLC environments.

Figure 4.7 also shows that:

- The η_t distribution shrinks at a reduced rate when α_η decreases.
- As $\frac{\Delta\alpha}{\alpha}$ goes to infinity, $\%\Delta VAR_{\alpha_\eta}[\eta_t]$ approaches -100% asymptotically.

These observations indicate that the investment in workforce learning can enhance the capability of manufacturers in controlling the performance of knowledge workforce in the

PLC environment. However, the investment has diminishing returns. When manufacturers meet the bottleneck of improving the learning capability of the workforce, they can switch to the investment on KWA for obtaining a better return on investment.

After examining the model of η w.r.t. the parameter space, KWA is shown to have potential for compensating for the insufficiency of manufacturers in maintaining a stably low η as they adopt timely production technology advances. KWA delivers this function through providing manufacturers a wide range of KW-capacity to accommodate the unstable and uncertain performance of the knowledge workforce. This function of KWA is especially important when η_t exhibits strong effects in terms of having either a large jump size or a high jump intensity, when the workforce learning capability is insufficient, and when the return on investment of the learning capability becomes small.

4.3 An Assessment of The RO Approach for Attaining KWA

This section further assesses whether modeling KWA as RO and optimizing KWA with the RO valuation techniques have merits. The evaluation is demonstrated under the demand uncertainty.

4.3.1 The Study Design

The RO-based KWA is generated from knowledge workforce planning using RO. There are many potential methods for workforce planning, and RO is not the only method that can attain KWA through workforce planning. However, the RO approach may have significant benefits over other approaches for attaining KWA. Thus, this section describes a comparison study for examining this assumption. The study is demonstrated under demand uncertainty, wherein the RO approach is compared to two other representative approaches in terms of the KWA they attain. The first approach plans the knowledge workforce through maximizing the cash flows anticipated upon a deterministic demand forecast over the PLC. The demand forecast describes the trend of demand movement during the PLC, so KW-capacity planned in this approach exhibits an adaption to the demand change during the PLC. The Bass (1969) model has been more widely used to forecast demand over the PLC, which actually uses DCF techniques. So, this approach is termed the Bass forecast (**BF**) approach, and the KWA attained using the BF is called BF-based KWA. In the BF approach KW-capacity at any time during the PLC is determined before the beginning, and KW-capacity adjustments will follow exactly the pre-planned schedule. The second approach is a chase-demand (**CD**) heuristic approach. The CD approach plans knowledge workforce through controlling yield within an appropriate range $[U_y, L_y]$. No demand model is needed in the CD approach. However, KW-capacity is adjusted dynamically with regard to demand changes. Thus, the CD approach acts as a greedy heuristic. The KWA attained in this approach is named as CD-based KWA.

There are two reasons why CD and BF are chosen to be compared with RO. First, These two approaches are representative. The Bass forecast model has been broadly used by both industry and academy for decades. The chase demand approach is simple, without any complex mathematical model, and it offers dynamics planning. Thus, it exhibits potential advantages in dynamic systems and has been reported to be used in industry. If the RO approach has significant benefits over these two representative approaches, the significance of the work is clear. Second, the RO approach reduces the major limitations of these two approaches. The BF approach does not consider the unpredictability in demand, which is formally addressed in the RO approach. The CD approach is simple, whereas the RO approach is complex. However, if a significant improvements is made by RO, there will be a rationale for using a complex approach to plan the knowledge workforce in dynamic systems.

The comparison study is in three phases. A numerical example is generated in the first phase, and the three approaches for attaining KWA are compared in terms of the decisions (i.e., KW-capacity c_t and the production scale x_{wt}) and the outcomes (i.e., yield y_t, and net present value (NPV)). This numerical example pertains to the simulation of a random trajectory of demand over the PLC. The capacity planning, either in the RO approach or in the CD approach, is synchronous with the simulation. That is, the KW-capacity for the subsequent step and the production scale for the current step are determined immediately only after the current demand is observed. However, the capacity planning is finished before the simulation in the BF approach. The numerical example illustrates how the RO approach achieves an improvement.

The comparison in phase two is statistical. The simulation and the capacity planning as in phase one now are repeated for 30 times (to satisfy the assumption that a paired mean difference is either normal distributed or the number of paired observation is no less than 30). The NPVs obtained in the three approaches, NPV_{BF}, NPV_{CD} and NPV_{RO}, are recorded in each simulation, and they are compared on the following three aspects:

1. descriptive statistics(minimum, maximum, and mean),

2. distribution, and

3. paired t tests in $NPV_{CD} - NPV_{BF} = (vs. >)0$, $NPV_{RO} - NPV_{BF} = (vs. >)0$ and $NPV_{RO} - NPV_{CD} = (vs. >)0$.

These will illustrate if the RO approach creates the KWA rationally in response to the demand uncertainty, and will show statistically whether the RO approach generates the KWA pertaining to the highest production profit.

The study in phase three further examines the reliability of the RO approach in more uncertain environments through replicating phase two at two higher levels of the demand volatility σ. NPV_{BF}, NPV_{CD} and NPV_{RO} are recorded in 90 runs of simulation, with 30 replicates on each of the three levels of σ: 0.2, 0.4 and 0.6. Study items in phase 3 includes:

1. the change in distribution, and

2. the change in the 95% confidence intervals of $NPV_{CD} - NPV_{BF}$, $NPV_{RO} - NPV_{BF}$, and$NPV_{RO} - NPV_{CD}$.

4.3.2 Demonstrating The RO Approach in A Numerical Example

This thesis uses a numerical example to given a first insight into how the RO approach makes workforce planning different. To make the simulated random trajectory of demand over the PLC pertain to the KW-capacity planned for it in any of the BF, CD and RO approach, they are together illustrated in 4.8. Demand is represented by a thin solid line, and is projected on the variables t and D_t in Figure 4.8. The KW-capacity obtained by the three approaches are projected on the variables t and c_t in the figure, with the BF, CD and RO approaches being indicated by a dashed line, a dotted line and a solid line, respectively.

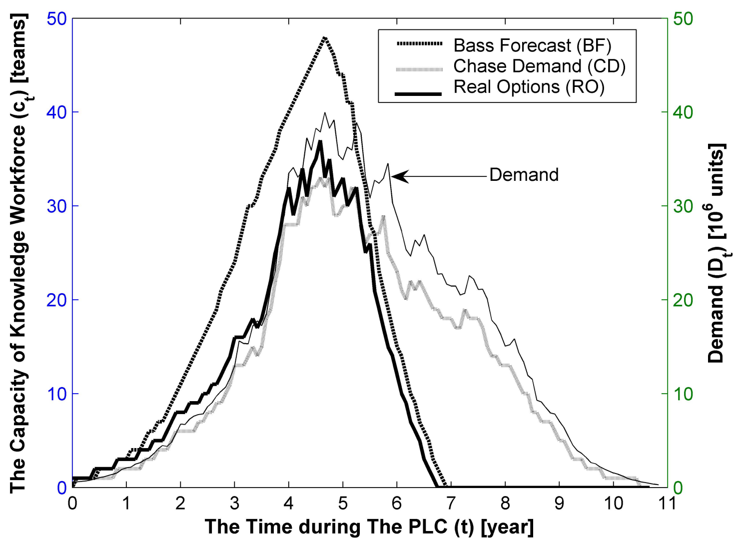


Fig. 4.8. Comparison of BF, CD and RO in terms of KW-capacity

The 4.8 shows that the KW-capacity in the BF approach clearly deviates from the random trajectory of demand in early in the PLC. We recall that the Base forecast does not contain information on demand uncertainty. The KW-capacity attained through either the CD approach or the RO approach exhibits a more satisfaction to demand when the sales prices is high. This observation informs us that the CD approach and the RO approach remedy the deficiency of the BF approach. However, the figure displays that the KW-capacities attained by the BF approach and by the RO approach drop quickly in the late PLC, no longer satisfying all the demand. The workforce planning in the two approaches hold a long-term view for earning production profit, and they base this view on the maximization of the expected cash flows throughout the PLC. Thus, the observation illustrates the short-sighted view that the CD approach takes in workforce planning.

To display what changes the RO approach makes, compared to either the BF approach or to the CD approach, on the production scale decision, Figure 4.9 illustrates the differences in the number of periodic wafer starts, Δx_{Wt}, over the PLC, with the solid line indicating the change that the RO approach makes compared to the CD approach and with the dotted line indicating the change compared to the BF approach.

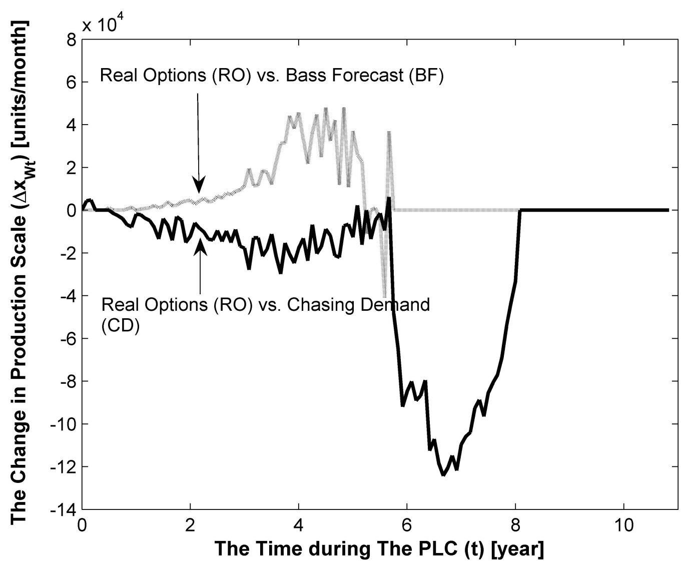


Fig. 4.9. Changes in The Production Scale RO Makes Compared to BF and CD

Figure 4.9 shows that the production scale is less built in the RO approach than in the BF approach in the early PLC when excess KW-capacity is planned using the BF approach. The figure also shows that the production scale is less in the RO approach than in the BF approach in the late PLC when excess KW-capacity is built in the CD approach. The observations indicate that not only the KW-capacity but the production scale is planned appropriately in the RO approach.

To show what changes the RO approach brings to yield compared to the BF approach and to the CD approach, the yields attained by the three approaches are projected on the two variables t and y_t in Figure 4.10, with BF, CD and RO being indicated by the dashed line, the dotted line and the solid line, respectively.

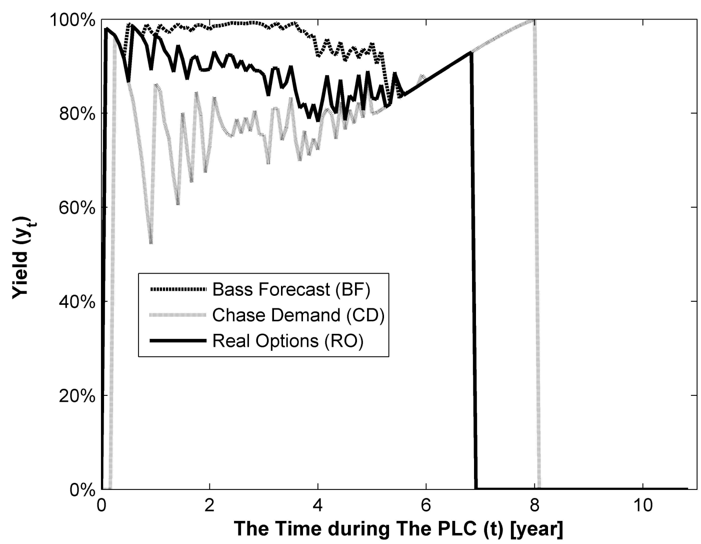


Fig. 4.10. The Comparison of BF, CD and RO in terms of Yield

Figure 4.10 shows that the yield in the RO approach is lower than in the BF approach in early PLC when excess KW-capacity is built in the BF approach. Figure 4.10 displays that the yield in the CD approach is lower and less stable than in the RO approach in the early PLC, and the difference takes almost 6 years to be eliminated. The figure further indicates a delay of production close in the CD approach. The RO approach exhibits rationality in cultivating KWA, which is manifested by the relatively table and economical yield attained from the RO approach.

The improvements that the RO approach achieves compared to the BF approach and to the CD approach are straightforward measured by the NPVs achieved in the three approaches. In this example, $NPV_{BF} = \$11.2B$, $NPV_{CD} = \$11.4B$ and $NPV_{RO} = \$13.7B$, respectively. NPV_{CD} is only 2.4% higher than NPV_{BF}, whereas NPV_{RO} is 22.7% higher than NPV_{BF} and 19.9% higher than NPV_{RO}. Thus, the RO approach performs the best in this example, and the CD approach display a slight advantage over the BF approach.

Through observing the changes that the RO approach brings to the decisions and to the outcomes compared to the BF approach and to the CD approach in this example, the RO approach is shown improving knowledge workforce planning in PLC environments.

4.3.3 Capability of Attaining Profits under Uncertainty

NPV_{BF}, NPV_{CD} and NPV_{RO} are replicated in 30 runs of simulation, and the data are used for comparing the attitudes that the three approaches hold to risks associated with uncertainty in workforce planning. The minimum, mean and maximum of NPVs in each approach are listed in Table 4.2. The table shows, although the BF approach does not generate the smallest minimum NPV among the three approaches, it results in the smallest mean and maximum NPV. Behind this observation is the fact that the BF approach does not consider the possible deviations from the expected demand in workforce planning. The maximum NPV is almost doubled in the CD approach relative to the BF approach. However, the minimum of NPV_{CD} is negative, which is \$10.2B less than the minimum of NPV_{BF}. This indicates that, when the CD approach betters the BF approach, it also removes the advantage of the BF approach. As a result, the mean of NPV_{CD} \$24.0B does not exhibit a clear rise when compared to the mean of NPV_{BF} \$21.0B. The RO approach generates the highest minimum, mean and maximum NPVs among the three approaches, indicating that the RO approach achieves an improvement over both the BF approach and the CD approach.

Table 4.2.
Descriptive Statistics of The NPVs attained in BF, CD and RO (in Billion)

	NPV_{BF}	NPV_{CD}	NPV_{RO}
minimum	\$1.5	-\$8.7	\$7.7
mean	\$21.0	\$24.0	\$29.8
maximum	\$35.7	\$70.7	\$84.1

Further, the distributions of NPV_{BF}, of NPV_{CD}, and of NPV_{RO} are fitted respectively using the 30 replicates of NPV in that approach. Figure 4.11 illustrates the NPV distributions within the data range. The figure clearly illustrates important observations. First, the BF approach generates the most narrow NPV distribution, which confirms the fact that the BF approach is the most conservative approach of attaining KWA. Second, the CD approach generates the widest NPV distribution. However, NPV_{CD} and NPV_{BF} have a similar mode. Thus, the CD approach is the most aggressive and the most risky approach of attaining KWA. Last, the NPV_{RO} distribution exhibits a clear shift towards the large side compared to the other two, indicating that the RO approach is the most rational among the them. When countering threats accompanied with uncertainty, the RO approach is safer than the CD approach, and demonstrates less sacrifice than the BF approach. When taking opportunities associated with uncertainty, the RO approach is less aggressive than the CD approach, and is less conservative than the BF approach.

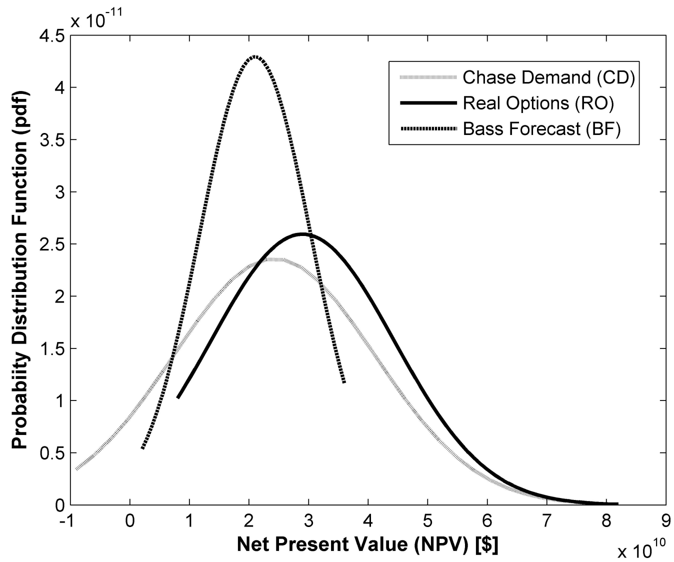


Fig. 4.11. NPV Distributions in The BF, CD and RO Approaches

The BF, CD and RO approaches of attaining KWA are finally compared using paired t tests. Items of test and results are listed in Table 4.3. The p-Value of the paired t test for $NPV_{CD} - NPV_{BF} = 0$ is 0.112, greater than 5%, and the 95% lower bound of the mean difference is less than zero. So, the CD approach is not statistically better than the BF approach at a significant level of 5%. However, for any other paired t test, the p-value is 0.000, and the 95% lower bound of mean difference is greater than zero. Thus, the RO approach generates the highest expected NPV with statistical significance.

The results of the paired t test indicate that the KWA attained from the RO approach responds to risks the best.

Table 4.3.
Paired t Tests on NPVs in BF, CD and RO approaches

Test Item	95% **LB of Mean Difference**	**P-Value**
$NPV_{CD} - NPV_{BF}$ =(vs.>)0	-\$1.09B	0.112
$NPV_{RO} - NPV_{BF}$ =(vs.>)0	\$5.28B	0.000
$NPV_{RO} - NPV_{CD}$ =(vs.>)0	\$3.53B	0.000

4.3.4 Robustness in More Uncertain Environments

NPV_{BF}, NPV_{CD} and NPV_{RO} are based on 90 simulated runs, with 30 runs at each of three levels of demand volatility: 0.2, 0.4 or 0.6. The data are used to compare the reliabilities of the three approaches in more uncertain environments. The distributions of NPV_{BF}, of NPV_{CD} and of NPV_{RO} are fitted at three levels of demand volatility, and illustrated in Figure 4.12. The figure shows that an increase in demand volatility makes only the NPV_{BF} distribution and the NPV_{CD} distribution shift substantially towards the low NPV side. This indicates that, of the three, only the RO approach produces reliable KWA in highly volatile environments.

Further, to examine how the agility-driven capabilities of the three approaches are impacted by the uncertainty scale, the 95% CIs of $NPV_{CD} - NPV_{BF}$, of $NPV_{RO} - NPV_{BF}$, and of $NPV_{RO} - NPV_{CD}$ are obtained and shown in Table 4.4. First, the 95% CI of $NPV_{CD} - NPV_{BF}$ contains zero at all the levels of demand volatility, whereas 95% CIs of $NPV_{RO} - NPV_{BF}$ and of $NPV_{RO} - NPV_{CD}$ are greater than zero at any

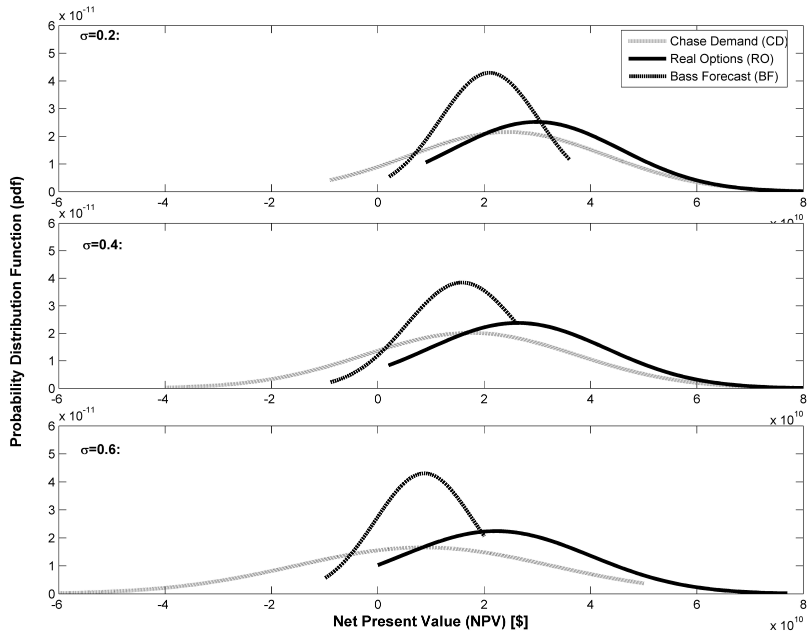


Fig. 4.12. Reliabilities of the BF, CD and RO Approaches in More Volatile Environments

level of demand volatility. This confirms the observations in Figure 4.11 that the RO approach generates reliable KWA in the more uncertain environments. Furthermore, a linear regression model is fitted to show how much improvement the RO approach makes compared to the other two approaches in more uncertain environments. The response variable is $E[\Delta NPV]$, the expected NPV increase that the RO approach compares to any other approach. The predictor variables are the demand volatility, σ, (at 0.2, 0.4 and 0.6) and the pair of agility-driven approaches, *pair*, (it is coded, with -1 indicating $E\left[NPV_{RO}\right] - E\left[NPV_{BF}\right]$ and 1 indicating $E\left[NPV_{RO}\right] - E\left[NPV_{CD}\right]$). The regression model is obtained in Table 4.5. The coefficient of the predictor variable *pair* is 0.101, indicating that the between-pairs difference is not important at a 5% significance level. As shown in Table 4.5, the regression model is $E\left[\Delta NPV\right] = 4.2 + 14.5\sigma$ in billion. The

Table 4.4.
95% CI of Differences in NPVs in BF, CD and RO approaches

	95% **CI of Mean Difference in NPVs**		
	$\sigma = 0.2$	$\sigma = 0.4$	$\sigma = 0.6$
$NPV_{CD} - NPV_{BF}$	$\$3.0B \pm \$4.9B$	$\$2.0B \pm \$6.8B$	$\$0.2B \pm \$6.6B$
$NPV_{RO} - NPV_{BF}$	$\$8.8B \pm \$4.2B$	$\$10.6B \pm \$4.9B$	$\$13.2B \pm \$6.9B$
$NPV_{RO} - NPV_{CD}$	$\$5.8B \pm \$2.7B$	$\$8.6B \pm \$4.5B$	$\$13.0B \pm \$4.9B$

model informs us that the RO approach raises the expected NPV, compared to either the CD approach or the BF approach, at a rate of 14.5 billion per unit of demand volatility.

Table 4.5.
Regression Models of The Expected NPV Increase RO Makes compared to BF or CD

Regression Model	**P-Value**		R^2	R^2_{adj}
	Coef of *pair*	Coef of σ		
$E\left[\Delta NPV\right](billion) = 4.2 - 0.867pair + 14.5\sigma$	0.102	0.008	93.9%	89.8%
$E\left[\Delta NPV\right](billion) = 4.2 + 14.5\sigma$	N/A	0.012	82.2%	78.5%

4.4 An Evaluation of The Profit Growth from RO-based KWA

The previous two sections have shown that RO-based KWA best benefits high-tech industries in PLC environments in the previous two sections. This section subsequently evaluates the expected profit growth that the RO-based KWA generates from various sources of uncertainty in PLC environments.

4.4.1 The Study Design

The profit growth from KWA is measured by KWA value. V_{AD} and $V_{A\eta}$ denote the KWA values under demand uncertainty and in WK dynamics, respectively. To examine if KWA value is considerable in either source of uncertainty, V_{AD} and $V_{A\eta}$ are separated. In evaluation of V_{AD}, η_t is assumed as a deterministic function of time and D_t is the underlying process. KWA thereby copes with only demand uncertainty, and gives V_{AD}. To assume D_t is deterministic in evaluation of $V_{A\eta}$ is unrealistic. However, if KWA copes with demand uncertainty with homogeneous policy, $V_{A\eta}$ can still be attained. Thus, in evaluation of $V_{A\eta}$, both D_t and η_t are underlying processes. $V_A\eta$ is disclosed by coping with WK dynamics in different ways and yet in the same way for demand uncertainty.

Designing The Study for Measuring V_{AD}

NPV_{FC} is the NPV given by an optimal fixed KW-capacity, and NPV_{RO} is the NPV after adopting RO-based KWA. KWA value under demand uncertainty, V_{AD}, measures the expected NPV increment after adoption of RO-based KWA, and is calculated by taking the difference between the expected value of NPV_{RO} and the expected value of NPV_{FC} in Equation (4.8).

$$V_{AD} = E\left[NPV_{RO}\right] - E\left[NPV_{FC}\right] \tag{4.8}$$

$E\left[NPV_{FC}\right]$ in Equation (4.8) is obtained through maximizing the expected NPV with respect to demand modeled in Equation (3.4). Decision variables in the optimization are the fixed KW-capacity and the duration of it (i.e., the time interval from the beginning of the PLC to where the capacity becomes zero). $E[NPV_{RO}]$ in Equation (4.8) is estimated using the mean value of 30 replicates of NPV_{RO}.

Further, V_{AD} can be separated into two parts, as in Equation (4.9).

$$V_{AD} = V_{RO} + V_{BI} \tag{4.9}$$

The first part in Equation (4.9), V_{RO}, is the increment of the expected NPV that KWA obtained the demand stochasticity. The second part, V_{BI}, is the increment of the expected NPV that KWA attains from Bayesian information on T_m. Equation (4.10) shows V_{RO} is calculated by taking the difference between $E[NPV_{PR}]$, which is the expected NPV using RO valuation but with no Bayesian information on T_m (i.e., μ_{T_m}, the prior information on T_m, is used demand model), and $E[NPV_{FC}]$.

$$V_{RO} = E[NPV_{PR}] - E[NPV_{FC}] \tag{4.10}$$

V_{AD} is evaluated on two aspects.

1. V_{AD} is estimated at three levels of σ: 0.2, 0.4 and 0.6, and at each level the t test is used to examine whether V_{AD} is greater than zero with statistical significance. If V_{AD} is greater than zero across the wide range of σ, the quantitative relation between V_{AD} and σ will be examined.

2. V_{AD} is separated as V_{RO} and V_{BI} at the three levels of σ to identify the major contributor of generating V_{AD}, RO or the Bayesian estimation.

Designing The Study for Measuring $V_{A\eta}$

$V_{A\eta}$, measures the expected NPV increment from adopting RO-based KWA with respect to WK dynamics. If $NPV_{\overline{\eta}}$ and NPV_{η} denote the NPVs before and after using RO-based KWA to handle WK dynamics (i.e., the unreliable performance of the knowledge workforce in adoption of production technology advances), respectively, $V_{A\eta}$ is evaluated by taking the difference between the expected value of NPV_{η} and the expected value of $NPV_{\overline{\eta}}$, as in Equation (4.11).

$$V_{A\eta} = E\left[NPV_{\eta}\right] - E\left[NPV_{\overline{\eta}}\right] \tag{4.11}$$

$E\left[NPV_{\eta}\right]$ in Equation (4.11) is evaluated on a multi-layer lattice, whereas $E\left[NPV_{\overline{\eta}}\right]$ is on a single-layer lattice.

The evaluation of $V_{A\eta}$ involves examining whether a considerable profit growth is attained when RO-based KWA is used to handle difficulties associated with WK dynamics. $V_{A\eta}$ is possibly impacted by the uncertainty scale of the η_t jumps. The changes in the jump size r_{η}, in the jump intensity λ_{η}, and in the reverting speed after jump α_{η} have been shown in Section 4.2.2 to vary the distribution of η_t. So, the evaluation takes the three parameters as factors, and each factor is represented by three levels:

- r_{η} (%): 25, 50 and 75;
- λ_{η} (year^{-1}): 0.25, 0.5 and 0.75;
- α_{η} (year^{-1}): 0.4, 0.7, 1.0.

Because of the computational complexity, the evaluation examines the relation between $V_{A\eta}$ and one factor at one time. In addition, the procedure of learning information about T_m is omitted in the evaluation of $V_{A\eta}$, so the evaluation takes T_m as a random block and chooses three levels for T_m: 3 years, 5 years and 7 years. The value of T_m falls in this range with 95% confidence.

4.4.2 KWA Value under Demand Uncertainty

Figure 4.13 illustrates the estimate of V_{AD}, the KWA value under demand uncertainty, and the 95% CI of the estimate at three levels of demand volatility: 0.2, 0.4 and 0.6. Furthermore, the estimates of V_{AD} are separated as V_{RO} (indicated by dark grey) and V_{BI} (indicated by light grey) in Figure 4.13.

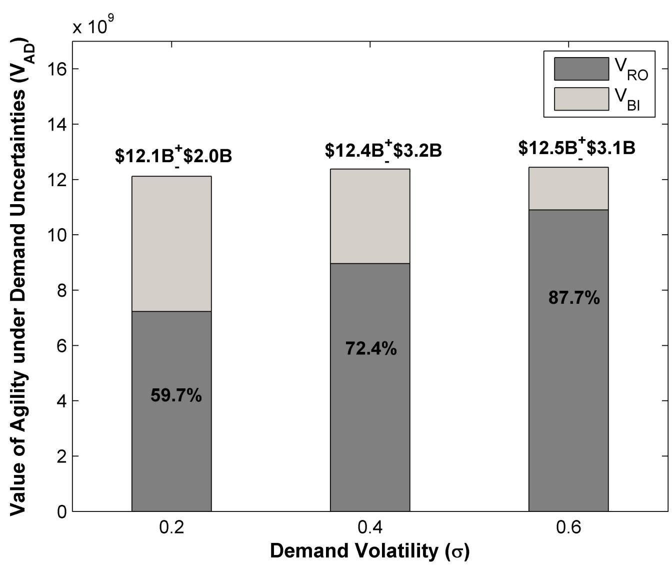


Fig. 4.13. Changes in V_{AD} and in Composition over A Range of Demand Volatility

Figure 4.13 shows that the 95% CI of the estimate of V_{RO} is consistently larger than zero across the range of demand volatility in the figure, and the expected profit growth from KWA under demand uncertainty is in units of 10 billion. Figure 4.13 further shows the 95% CIs at the three levels of demand volatility overlap, so the increase of demand volatility does not change V_{AD} at the 5% significance level. However, the figure displays the clear relations between σ and V_{RO}/V_{BI}, the components of V_{AD}. That is, when the demand volatility rises from 0.2 to 0.6, the ratio of V_{RO} in V_{AD} rises from 59.7% to 87.7% at roughly a constant rate. The observations informs us that expected profit growth that RO-based KWA generates is positive, even in highly volatile environments. The observations further indicates that RO plays an important role in generation of V_{AD}, and the role of RO is indispensable when demand movement becomes more difficult to be predicted. Meanwhile, the figure shows that the the ratio of V_{BI} in V_{AD} decreases over the range of demand volatility. Bayesian estimate of T_m depends on the demand distribution (see Equations 3.9-10), and a wide demand distribution may lower the capability of Bayesian estimation. The demand distribution is wide when the demand volatility is high, so it is possible that V_{BI} decreases over the demand volatility.

The accuracy of V_{RO} pertains to whether the underlying process is properly modeled. Thus, an experiment is created to compare the demand model developed in this thesis and the Bollen (1999) model in terms of the expected NPVs they generate. The Bollen model does not build the relation between the drift rate in demand and the length of PLC, and thus it provide biased information for knowledge workforce planning. So, the expected NPV given by the demand model in Equation 3.4 is higher than the expected NPV given by the Bollen model. The increase of the expected NPV, $\Delta E[NPV]$, is chosen as the response variable in the experiment, and the time of demand maturity, T_m, is a random factor. Since both models are underlying process serving RO valuation, demand volatility, σ, possibly does not affect the improvement of the proposed demand model. To examine this assumption, σ is taken as another factor in the experiment. Three levels are chosen for each factor:

- T_m: 3 years, 5 years and 7 years, and the value of T_m falls in this range with a 95% confidence;
- σ: 0.2, 0.4 and 0.6.

Results of the experiment are illustrated in Figure 4.14. The Figure shows that the expected NPV increases after substitution of the Bollen model with the proposed demand model. Figure 4.14 further suggests that increment of the expected NPV rises substantially if the PLC length shrinks, possibly due to price erosion. The relation between the $\Delta E[NPV]$ and T_m is relatively homogeneous across the three levels of demand volatility, indicating that σ is not an important predictor variable.

Regression models are fitted in Table 4.6 to confirm and analyze the observations from Figure 4.14. The coefficient of σ in the first regression model in Table 4.6 is 0.671, so σ is verified as an unimportant factor. The reason for this may be that both the demand model and the Bollen model are Geometric Brownian motion processes and provide accurate information on the demand stochasticity. The regression model ultimately only contains one predictor variable, T_m, and the model is shown in Table 4.6. The model informs us that the replacement of the Bollen model by the proposed demand model

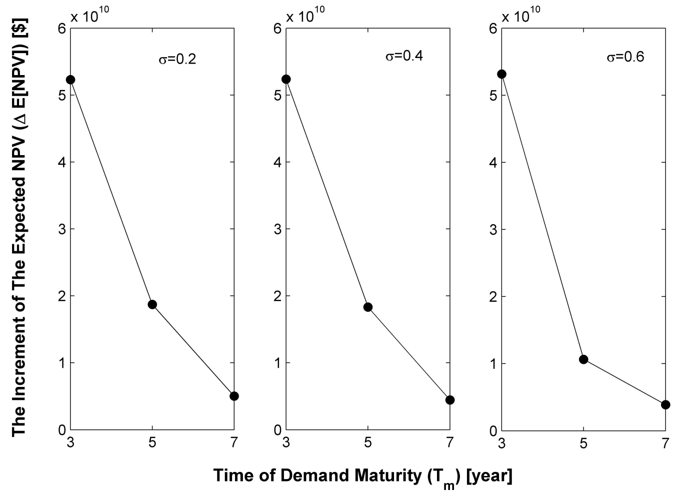


Fig. 4.14. Comparing The Proposed Demand Model to The Bollen Model

increases the expected NPV, and the increment raises about $\$6B$ for every one year that the PLC length reduced.

4.4.3 KWA Value in WK Dynamics

Figure 4.15 displays the results of the experiment which is designed for evaluating $V_{A\eta}$, the KWA value from coping with WK dynamics. The figure is composed of three plots, which illustrate the relations between $V_{A\eta}$ and each one of the parameters related to the η_t jumps: the jump size r_η, the jump intensity λ_η, and the reverting speed after jump α_η. The left plot displays $V_{A\eta}$ in nine treatments which are distinguished by the three levels of r_η (25%, 50% and 75%) at the three levels of T_m (3years, 5years and 7years). The other two plots are similarly constructed. The minimum of λ_η in Figure 4.15 is no less than one billion, indicating that to handle unreliable performance of the knowledge workforce using KWA will gain a considerable financial reward. Figure

Table 4.6.
Regression Analysis of The Expected NPV Increase from Modeling Demand Properly

Regression Model	P-Value		R^2	R^2_{adj}
	Coef of σ	Coef of T_m		
$\Delta E[NPV](billion) = 87.3 - 7.0\sigma + 12.0T_m$	0.671	0.000	90.9%	87.8%
$\Delta E[NPV](billion) = 84.5 - 12.0T_m$	N/A	0.000	90.6%	89.2%

4.15 further shows that $V_{A\eta}$ will rise when r_η increases, when λ_η increases, or when α_η decreases. The observation indicates the value of agility is high when the η_t distribution is wide, which is consistent to the analytical results in Section 4.2.2. In addition, the figure displays a clear decrease in $V_{A\eta}$ when T_m increases, indicating that the role of KWA is crucial in short PLC scenarios.

To quantify the relations observed in Figure 4.15, three regression models are fitted and listed in Table 4.7. Each regression model corresponds to one plot in Figure 4.15. In all of the three regression models, the coefficient of T_m is -1.4 and the p-Value for the coefficient is 0.000, indicating that at the significance level of 0.000 $V_{A\eta}$ raises \$0.7B for every one year that the PLC reduces. The coefficient of r_η is 4.3 in the first regression model, and the p-value for the coefficient is 0.02. So, at 2% significance KWA value will increase \$0.043B when the jump size increases 1%. The other two regression models inform us that, with 98% confidence the growth of $V_{A\eta}$ is \$0.62B if the jump intensity increases 0.1 year^{-1}, or with 95% confidence it is \$0.24B if the reverting speed after jump decreases 0.1 year^{-1}.

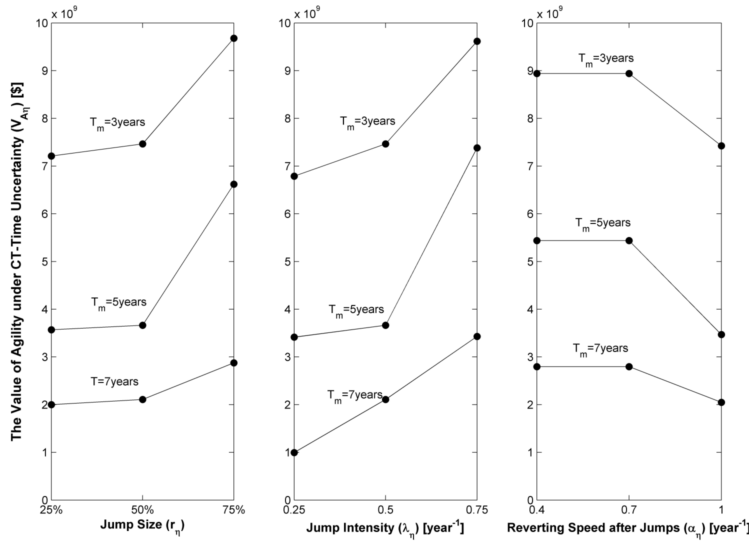


Fig. 4.15. The relation between $V_{A\eta}$ and $r_\eta/\lambda_\eta/\alpha_\eta$ at Different lengths of PLC

4.5 An Examination of Numerical Schemes

Two numerical schemes are particularly designed for accommodating to the research problems of this thesis. They are the dynamic decision/state space in Section 3.5.5 and the hybrid tree in Section 3.6.2. The former is for speeding up the dynamic programming (**DP**) procedure, and the latter is for reducing the computational complexity of binomial tree. The effectiveness of the designs is examined in this section.

4.5.1 The Study Design for Examining Numerical Methods

The Study on The Dynamic Decision/State Space

To show that the dynamic decision/state space speeds up the DP procedure without significantly sacrificing the solution accuracy, the dynamic decision/state space is compared to the fixed decision/state space in terms of the expected NPV, $E[NPV_{RO}]$,

Table 4.7.
Regression Models of $V_{A\eta}$

Factor	Fitted Model of $V_{A\eta}$ (billion dollars)	P-Value		R^2	R^2_{adj}
		block(T_m)	**factor**		
r_η	$V_{A\eta} = 10.1 - 1.4T_m + 4.3r_\eta$	0.000	0.02	93.3%	91.1%
λ_η	$V_{A\eta} = 9.1 - 1.4T_m + 6.2\lambda_\eta$	0.000	0.02	95.4%	93.8%
α_η	$V_{A\eta} = 13.5 - 1.4T_m - 2.4\alpha_\eta$	0.000	0.05	94.4%	92.6%

and the computational time, T_{cpt}. The computational complexity of the DP procedure on a binomial lattice is a function of the decision time horizon, and thus the two decision/state spaces are compared at seven different lengths of PLC, from $T_m = 2$ to $T_m = 8$ and the value of T_m falls in this range with 99.6% confidence. At each level of T_m, a binomial lattice with the decision time horizon of $2T_m$ is built to represent demand during the PLC. The backward DP procedure is conducted on the lattice twice, and each time a different decision/state space is used. The changes in $E[NPV_{RO}]$ and in T_{cpt} after adopting the dynamic decision/state space are recorded for analysis.

Studies on The Hybrid Tree

The ends of the tree phase (N_T) and of the lattice-like phase (N_L) are important designs of the hybrid tree, and they are results of trading off efficiency and accuracy. The hybrid tree in this thesis has seventeen steps. N_T and N_L are chosen as the end of step six and the end of step ten, respectively. An experiment is designed to evaluate whether the values of N_T and of N_L are properly chosen. The expected NPV, $E\left[V_{A\eta}\right]$, is chosen as the response variable in the experiment. N_T and N_L are the two factors, and three levels are chosen for each one:

- N_T (steps): 5, 6 and 7;

- N_L (steps): 8, 10 and 12.

$\Delta T'$, the step size in the numerical approximation of η_t, is another important design of the hybrid three. Although the solution accuracy is improved as $\Delta T'$ decreases, the computational time increases substantially. So, the computational efficiency and the solution accuracy have to be considered in the design of $\Delta T'$. $\Delta T'$ is chosen as a half year, so a ten-years PLC at most has seventeen steps. To examine if $\Delta T'$ is well calibrated, KWA value in WK dynamics, $V_{A\eta}$, and the computational time, T_{cpt}, are compared at two levels of $\Delta T'$: $\frac{1}{2}$ years and $\frac{1}{3}$ years.

4.5.2 Examining The Dynamic Decision/State Space

Table 4.8 displays the losses of the expected NPV and the reductions of the computational time after substituting the fixed decision/state space with the dynamic decision/state space at seven levels T_m. Results in Table 4.8 shows that after using

Table 4.8.
Examining The Effectiveness of Dynamic Action/State Space

T_m (year)	**Loss of** $E[NPV_{RO}]$	**Reduction in** T_{cpt}
2	1.28%	89.45%
3	0.32%	90.02%
4	0.15%	89.41%
5	0.06%	89.31%
6	0.02%	89.58%
7	0.00%	89.94%
8	0.00%	90.62%

the dynamic decision/state space the computational time is reduced by at least 89%, whereas the expected NPV is lowered by at most 1.5%. The observation suggests that the dynamic decision/state space substantially speeds up the DP procedure without significantly sacrificing accuracy.

4.5.3 Examining The Design of The Hybrid Tree

Figure 4.16 illustrates the main effect plots of $V_{A\eta}$ for examining the designs of N_T, the end of the tree phase, and of N_L, the end of the lattice-like phase. Figure

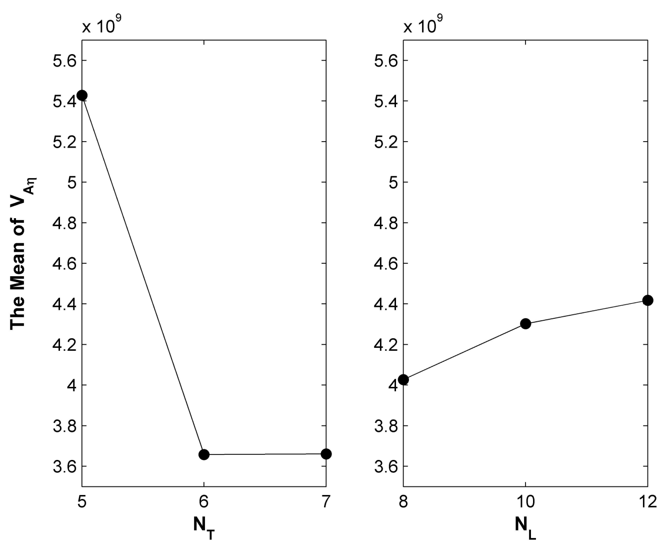


Fig. 4.16. Main Effect Plots for $V_{A\eta}$ in Design of Hybrid Tree

4.16 shows that $V_{A\eta}$ is lowered when N_T increases, and $V_{A\eta}$ rises when N_L increases. The observation indicates that the substitution of the binomial tree with the lattice-like structure leads to the overestimation of $V_{A\eta}$, and the substitution of the binomial tree with the strip structure causes the underestimation of $V_{A\eta}$. By comparing the two main effect plots, $V_{A\eta}$ is found to be more sensitive to choices of N_T than to N_L. Moreover, the main effect plots show that $V_{A\eta}$ almost stops decreasing when N_T is greater than six, and the pace of $V_{A\eta}$ increase is substantially reduced when N_L is great than ten. Observations in Figure 4.16 indicate that $N_T = 6$ and $N_L = 10$ are appropriate for the hybrid three.

Two choices of $\Delta T'$, the step size in the numerical approximation of η_t, are compared in Table 4.9. The comparison in Table 4.16 shows that the probability that more

Table 4.9.
Comparision of Step Sizes in Approximation of η_t

Step Size ($\Delta T'$)	$PX = 0$	$PX = 1$	$PX \geq 2$	N_T	N_L	$V_{A\eta}$($)	T_{cpt}(sec.)
$\frac{1}{2}$year	77.9%	19.5%	2.7%	6	10	3.7B	34634
$\frac{1}{3}$year	84.7%	14.1%	1.2%	9	15	5.7B	151889

than one jump occurs is reduced from 2.7% to 1.2% when $\Delta T'$ is reduced from $\frac{1}{2}$ years to $\frac{1}{3}$ years. As a result, the expected NPV increases $\$2B$ at a cost increasing the computational time by a factor of five. Results in Table 4.9 suggests that, to attain a higher expected production profit through reducing the step size in the numerical approximation of η_t, some alternate computing techniques maybe needed.

Chapter 5

Conclusions and Future Work

This thesis investigated the reason why the product life cycle (**PLC**) phenomenon placed significant pressures on high-tech industries. High-tech industries relied heavily on the knowledge workforce in transferring cutting-edge technologies into products. However, market changes and production technology advances happened frequently and unpredictably during the PLC, causing difficulties in predicting an appropriate demand on knowledge workforce and in maintaining reliable performance. Knowledge workforce planning in PLC environments thereby was not easy, and this made high-tech industries apprehensive of the unexpected changes and incapable of matching the rapid pace of change.

This thesis identified knowledge workforce agility (**KWA**) as a desirable advantage of high-tech industries which operate in PLC environments. This thesis found that previous research on KWA was limited, and the linkage of KWA to workforce flexibility was incomplete. It thereby accomplished several critical tasks to have realized the advantage of KWA. This thesis chose real options (**RO**) as the approach of exploiting KWA since it found that RO captured the essence of KWA– options in manipulating knowledge capacity, a human asset, or a self-cultivated organizational capability for pursuing interests associated with change. Accordingly, this thesis formulated workforce knowledge (**WK**) dynamics in adoption of technology advances and market demand change as underlying stochastic processes during the PLC. It modeled KWA as capacity options in a knowledge workforce and developed a RO approach of workforce training (either initial or continuous) to generate the options. This thesis finally implemented RO valuation methods and techniques to optimize KWA and to maximize the expected reward from KWA.

Results from an analytical examination of the underlying process models with respect to the parameter space identified that KWA had potential to reduce negative impacts and generate opportunities in an environment of volatile demand, and to compensate unreliable performance of knowledge workforce in adoption of technology advances. The benefits of KWA were especially important when confronting highly volatile demand, a low initial adoption level, shrinking PLCs, a growing market size, intense and frequent WK dynamics, insufficient learning capability of employees, or diminishing returns from investments in learning. Furthermore, comparisons among three approaches of attaining KWA under demand uncertainty showed that RO-based KWA was better than KWA derived either from the chase-demand heuristic or from the Bass forecasting model, in that RO-based agility leaded to a stably higher yield, to a consistently larger NPV, and to a NPV distribution that was more robust to highly volatile demand. Thus, RO-based KWA made high-tech industries operate more effectively. Finally, a quantitative evaluation of the KWA value verified that RO-based KWA created a considerable profit growth, either under uncertainty in demand or in WK dynamics. In evaluation, RO modeling and the RO valuation were identified to be crucial in creation of KWA value. This thesis illustrated the effectiveness of the numerical methods used for solving the dynamic system problem.

5.1 Contributions

The research reported in this thesis was a clear demonstration of how to cultivate and optimize KWA in PLC environments with a view of RO. It provided an innovative solution for knowledge workforce planning in rapidly changing and highly unexpected environments. The work of this thesis was representative of studying KWA in PLC environments using quantitative techniques, where there was a dearth of quantitative studies in the literature. It exploited the benefits of KWA by optimizing KWA, and meanwhile, it boosted the profit growth through maximizing the expected reward from KWA. More specifically, the major contributions of the work were as follow.

1. The establishment of a model of the relation among KWA, RO and the PLC phenomenon, which probed into a new frontier of knowledge workforce management.

2. The formulizations of the demand model which combines diffusion theory and Brownian motion processes, and of the CTT model which directly addressed WK dynamics in adoption of technology advances. These model made optimization of KWA better informed.

3. The characterization of the role of knowledge workforce in unstable production environments, and the formulation of costs in attaining KWA. These calibrated every aspect that KWA impacted production and provided an approach for quantifying the benefits of KWA.

4. The development of a RO approach for workforce training. It delivered an optimal solution of generating KWA for high-tech industries, allowing for improved

knowledge workforce planning. The KWA attained via this approach leaded to a considerable profit growth compared to the agility derived either from the simple chase-demand heuristic or from the Bass forecasting model.

5. The avoidance of computationally expensive numerical procedures for attaining RO-based KWA, yet still keeping a reasonable accuracy in the solution.

5.2 Future Work

5.2.1 Limitations and Improvement Directions

This thesis research confronts some difficulties which are hard to be overcome. Limitations thereby exist, causing biases in the results obtained from the thesis research. Some future work is suggested by my thesis committee, which would either help reduce the limitations of the thesis work or probe into interesting directions. They are discussed in below.

1. To obtain a set of systematic data for fitting models and for examining the effectiveness of the thesis work. This thesis study is short of real data for fitting models. In addition, it has difficulties to obtain a whole data set for numerically demonstrating research results. Parameter values in Table 4.1 are not provided by one empirical study. Some of them are used in literatures and referred by this thesis. For the remains, this thesis has to make a reasonable guess. Fitting models with real data will help verify model formulations, justify model assumptions, and provide estimates of model parameters. The effectiveness of the new approach

proposed by this thesis can be demonstrated and examined by comparing it to the previous business solution.

2. To improve the computational efficiency for large size problems. Although the computational complexity has been reduced by this thesis, it still exhibits limitations. The problem of computational complexity will be more severe when confronting large size problems. Better designed algorithms or advanced computing techniques should be implemented to improve the computational efficiency.

3. To design sophisticated experiments capable of studying general statistical models and of conducting comprehensive sensitivity analyses. This thesis does not design experiments capable of studying multiple variables and their interactions because it is time consuming to fulfill the complex experiments. After the computational efficiency is improved, it will be possible to obtain more treatments. Thus, experiments should be redesigned for developing general statistical models or for conducting comprehensive sensitivity analyses, so accurate quantitative relations will be discovered through experimentation.

4. To investigate possibilities that KWA influences rather than yield in production. This thesis studies KWA at a planning level, and uses yield to characterize the impact of KWA on production. Yield improvement is an organizational learning. KWA not only benefits organizational learning, but individual learning. When the thesis work is extended to at an operational level, how KWA improves individual learning should be specified.

5. To develop methods for estimation of model parameters without history data. This thesis never discusses the estimation of model parameters without history data. Using models built on history data to inform decisions pertaining to long-term profits may be problematic because the future could be substantially different from the past or from the current. For example, the demand volatility may change significantly because of technology advances in the future, and the estimate based on history data is possibly invalid in such scenarios. Thus, how to estimate model parameters without history data or how to correct the estimates would be an interesting research topic.

5.2.2 Extensions of The Thesis Work

Possible extensions of this work are discussed below, but not are limited to them.

Extension to The Service Sector

Training and planning service providers are crucial in the service sector because service enterprises rely heavily on service providers to meet service requests. Many service providers are skill-based, so service enterprises are highly sensitive to changes in service requests. Seasonality has been a commonly observed PLC phenomenon in the service sector. It causes rapid and unanticipated changes in service requests, either in width or in depth. Thus, similar to the manufacturing sector, the service sector also bears pressures from the PLC phenomenon, and KWA may be beneficial.

KWA may be more desirable in the service sector than in the traditional manufacturing sector, and this has been manifested by following features of service enterprises.

- PLCs in the service sector are shorter than in the manufacturing sector.

- Service providers interact with the customers more directly and in more diversified channels in the service sector than in the traditional manufacturing sector.

- The calibration of the roles/performance of service providers is harder in the service sector than in the traditional manufacturing sector. On one hand, the output of service enterprises usually is intangible. On the other hand, investments on service quality improvement are instant and irreversible, whereas the rewards of the investments are long term and uncertain.

No surprisingly as extending the work of the thesis to the service sector, there will be many new elements. Some examples are below:

1. mathematical models of service systems that capture great realism and make the re-engineering of service systems well informed,

2. the schemes of training and allocating service providers in the re-engineering of service systems,

3. mechanisms for improving the performance of service providers, and

4. the measurements for the roles, the performance, and the impacts of service providers.

Extension to Endogenous Problems

The sales price and demand were treated as exogenous in this thesis, which is a common assumption in finance but is not in many other areas, because the assumption ignores a fact that knowledge workforce management can have marketing issues, technology advances with operations connected at the firm level. Thus, taking the sales price, demand, and WK dynamics as endogenous is more realistic, and this would be a valuable extension of this thesis since the role of KWA is broadened. After they are endogenized, the study of this thesis becomes a stochastic optimal control problem, including the following requirements:

1. the investigation of relations among workforce issues (e.g., availability, heterogeneity, quantity, quality, skill sets, training, teaming up, or the others), marketing issues (e.g., demand, and sales price), and technology issues (e.g., technology advances),
2. descriptive models of underlying processes, which exhibit how practices in knowledge workforce management influence marketing and technology issues, and in further, interact with operational decisions,
3. the formulation of the stochastic optimal control problem, and
4. algorithms for efficiently solving the optimal control problem, which states real-word decisions, and thus is complicated to be analyzed or solved.

The extension is not only just derived from this thesis but a valuable extension of the work which formulated the investment on knowledge workforce as a static optimal control problem[e.g., Mody (1989)].

Extension to Decisions on The Operational Level

This thesis discussed a knowledge workforce planning problem that involved one source of workforce and one task (or position). A natural extension is to use RO for studying scheduling problems, which is usually on an operational level and could be extremely complex. Although the extension is challenging, a promising future of it is foreseen. This is because some traditional approaches, such as mathematical programming, heuristic algorithm, and even the stochastic programming, have clear limitations in highly uncertain scenarios, whereas RO exhibit great advantages.

The most straightforward example is the cross training decision that various sources of workforce have to be trained to be capable of working on different tasks or a similar task but at different places (channels, stations, and the others). The decision maker has to determine when to train sources of workforce for various types of tasks (or positions). Demand (or service requests) come to different tasks (or positions), like some stochastic processes. Thus, the KW-capacity on each task/position, as well as the composition of the knowledge workforce, has to be changed to meet interests associated with change. From the view of the workforce, the skill sets of the individuals are expected to vary over time too. The goal of cross training in such scenario is to form a dynamic workforce constitution, whereby the workforce is consistently agile to the change in demand (or service requests).

Variations of this thesis

The research problem in this thesis can be solved using some other RO valuation methods or techniques. For example, this thesis approximately displayed the underlying processes using binomial lattice/tree, whereon the backward dynamic programming was conducted to optimize KWA. In practice, Monte Carlo simulation or partial differential equation also solve the problem well.

The work of this thesis will be varied if the underlying processes change. Several examples are discussed below.

1. WK dynamics is the only underlying process, which is a mean-reverting diffusion plus a stochastic jumping process. A multi-layers lattice can approximate it, and the computational complexity is the same as in this thesis.

2. WK dynamics is the only underlying process, which it is a mean-reverting diffusion process plus a stochastic jumping process. However, the jump size is not a constant. A multi-layers lattice can approximate this underlying process, but each layer has a unique distribution.

3. WK dynamics in 1 and demand are both underlying processes. A multi-layers lattice can still approximate the underlying processes, however, the computational complexity is higher than in this thesis.

4. WK dynamics as in 2 and demand are both the underlying processes. The RO valuation should be extremely complex.

The more sources of uncertainty a decision confronts, the more difficult it is to be analyzed and solved. This thesis would not recommend to generalize the problem as much as possible, since the generalization may be neither necessary nor computational efficient.

This thesis could not enumerate every subject or direction of future research. It demonstrated several to show the promising future of RO-based KWA. Future research opportunities could involve a combination of the abovementioned extensions, or they could be in some other interesting directions.

Appendix A

Itô's Lemma

The derivation of *Itô*'s Lemma has been provided in the extensive options literature [e.g.,Neftci (2000), and Hull (2003)].*Itô*'s Lemma is briefly introduced here as an important tool used in this thesis.

Itô's Lemma is a result of stochastic calculus for determining the differential of a function of certain stochastic process.

S_t represents a generalized Wiener process, as in Equation (A.1).

$$S_t = a(S_t, t)dt + b(S_t, t)dW_t. \tag{A.1}$$

If $f(S_t, t)$ is a function with continuous second derivatives, it is a generalized Wiener process too.

The *Itô*'s Lemma gives the differential of $f(S_t, t)$, as in Equation (A.2).

$$df = \left(\frac{\partial f}{\partial t} + a\frac{\partial f}{\partial S_t} + \frac{1}{2}b^2\frac{\partial^2 f}{\partial S_t^2} \right) dt + b\frac{\partial f}{\partial S_t}dW_t \tag{A.2}$$

Appendix B

Derivation of The Drift Rate Function μ_t

The spread of a new product in the market is similar to a diffusion process, so the diffusion theory is utilized in formulation of μ_t in this thesis. The expected cumulative demand over time, M, measures how saturated the product is in the market during the PLC. It usually exhibits an S-shape over the PLC, in general [e.g.Rosegger (1986)]. There are many sigmoid functions which can be used to describe the S-shaped pattern (e.g. logistic function, error function, or cumulative distribution functions of many statistic distributions). This thesis uses the cumulative distribution function (**cdf**) of normal distribution to model the cumulative demand over the PLC since this cdf can describe μ_t with a simple form. Using different sigmoid functions will not significantly alter the major work in derivation of η_t.

Demand, D_t, is modeled as a Geometric Brownian motion (**GBM**) in Equation (3.1), thus the natural logarithm of demand, $\ln D_t$, is a Brownian Motion (**BM**) process. The differential of $\ln D_t$ is obtained by applying *Itô*'s Lemma (see A), yielding the expression in Equation (B.1).

$$d \ln D_t = \left(\mu_t - \frac{1}{2}\sigma^2 \right) dt + \sigma dW_t, \tag{B.1}$$

The drift rate in demand can be derived easily from Equation (B.1).

$E[D_t]$ represents the expected demand at t. According to Equation (B.1), the differential of $\ln E[D_t]$ is obtained in below.

$$d \ln E[D_t] = \mu_t dt, \tag{B.2}$$

indicating that

$$\mu_t = \frac{E[D_t]'}{E[D_t]}. \tag{B.3}$$

$E[D_t]$ during the PLC is formulated as the distribution of expected cumulative demand over the PLC, as indicated in Equation (B.4).

$$E[D_t] = M\phi_t \tag{B.4}$$

ϕ_t in Equation (B.4) is the probability density of $E[D_t]$ which is normal distributed over time. Thus, ϕ_t models the bell shape of $E[D_t]$ over the PLC. The time of demand maturity, T_m, is where $E[D_t]$ reaches the peak, so T_m is the taken as the expected value of ϕ_t. $E[D_t]$ approaches zero at the either ends of the PLC (i.e., $t = 0$ or $t = T$), whereby T_m/β (β is a shape parameter whose value is around 3) is the estimate of the standard deviation of ϕ_t. Thus, the formulation of ϕ_t is obtained in Equation (B.5).

$$\phi_t = \frac{1}{\sqrt{2\pi}\frac{T_m}{\beta}} e^{-\frac{(t-T_m)^2}{2\left(\frac{T_m}{\beta}\right)^2}} \tag{B.5}$$

By plugging Equations (B.5) and (B.4) into Equation (B.3), the expression of μ_t is obtained, as in Equation (B.6).

$$\mu_t = \frac{\beta^2}{T_m} - \frac{\beta^2}{T_m^2} t. \tag{B.6}$$

β in Equation (B.6) is determined in evaluation of Equation (B.4) at $t = 0$ when $E[D_t]$ equals D_0. As a result, β is the solution of the implicit function of β in Equation (B.7).

$$f(\beta, M, D_0, T_m) = \beta e^{-\frac{\beta^2}{2}} - \frac{D_0 \sqrt{2\pi} T_m}{M} = 0. \tag{B.7}$$

In case that demand is discrete, coming at the interval of ΔT, D_0 in Equation (B.7) can be replaced by $D_0/\Delta T$ if ΔT is small enough.

Appendix C

Demand Model Fitting

According to the Equations (3.2) and (3.3), the relative change of demand in a time interval ΔT, $\frac{D_{i+1}-D_i}{D_i \Delta T}$ has a normal distribution $N(\frac{\beta^2}{T_m} - \frac{\beta^2}{T_m^2}t, \frac{\sigma^2}{\Delta T})$. Thus, the demand model in Equation (3.1) is verified through fitting a linear regression model using the time series $\frac{D_{i+1}-D_i}{D_i \Delta T}$. Results from running the regression procedure on SAS 9.1 are listed in below.

The REG Procedure

Dependent Variable: obs_mu_t

Number of Observations Read	43
Number of Observations Used	43

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	28.35302	28.35302	123.40	<.0001
Error	41	9.42034	0.22976		
Corrected Total	42	37.77336			

Root MSE	0.47934	R-Square	0.7506
Dependent Mean	0.30821	Adj R-Sq	0.7445
Coeff Var	155.52256		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	1.68233	0.14368	11.71	<.0001
t	t	1	-0.26174	0.02356	-11.11	<.0001

Test for Autocorrelation

Durbin-Watson D	1.512
Number of Observations	43
1st Order Autocorrelation	0.235

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.94498	Pr < W	0.0392
Kolmogorov-Smirnov	D	0.102408	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.068913	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.530497	Pr > A-Sq	0.1726

Appendix D

Derivation of η_t Formulation

To obtain the formulation of η_t through integrating $d\eta_t$ in Equation (3.11) is difficult. $f(\eta_t)$, a function η_t, is built in Equation (D.1) for derivation of η_t.

$$f(\eta_t) = \eta_t e^{\alpha_\eta t} \tag{D.1}$$

The differential of $f(\eta_t)$ is obtained in Equation (D.2).

$$df(\eta_t) = \frac{\partial f}{\partial t}dt + \frac{\partial f}{\partial \eta_t}d\eta_t + \frac{1}{2}\frac{\partial^2 f}{\partial \eta_t^2}(d\eta_t)^2 + \cdots = \alpha_\eta \eta_t e^{\alpha_\eta t}dt + e^{\alpha_\eta t}d\eta_t \tag{D.2}$$

By plugging Equation (3.11) into Equation (D.2), the differential of $f(\eta_t)$ turns to be the expression in Equation (D.3).

$$df(\eta_t) = e^{\alpha_\eta t}\alpha_\eta \eta_m dt + e^{\alpha_\eta t}\sigma_\eta dW_{\eta t} + e^{\alpha_\eta t} r_\eta dN_t. \tag{D.3}$$

Though integrating Equation (D.3), the expression of $f(\eta_t)$ is attained, as in Equation (D.4).

$$f(\eta_t) = f(\eta_0) + \eta_m\left(e^{\alpha_\eta t} - 1\right) + \sigma_\eta \int_0^t e^{\alpha_\eta s} dW_{\eta s} + r_\eta \int_0^t e^{\alpha_\eta s} dN_s \tag{D.4}$$

Replacing $f(\eta)$ with $\eta_t e^{\alpha_\eta t}$ in Equation (D.4), and then multiplying both sides of the equation by $e^{-\alpha_\eta t}$, η_t is obtained, as illustrated in Equation (3.12).

Appendix E

Derivation of The Mean and The Variance of η_t

$$
\begin{aligned}
E\left[\eta_t\right] &= E\left[e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\eta_m \right.\\
&\quad \left. +\sigma_\eta \int_0^t e^{\alpha_\eta (s-t)} dW_{\eta s} + r_\eta \int_0^t e^{\alpha_\eta (s-t)} dN_s\right]\\
&= e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\eta_m\\
&\quad +E\left[\sigma_\eta \int_0^t e^{\alpha_\eta (s-t)} dW_{\eta s}\right] + E\left[r_\eta \int_0^t e^{\alpha_\eta (s-t)} dN_s\right]\\
&= e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\eta_m\\
&\quad +\sigma_\eta \int_0^t e^{\alpha_\eta (s-t)} E\left[dW_{\eta s}\right] + r_\eta \int_0^t e^{\alpha_\eta (s-t)} E\left[dN_s\right]\\
&= e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\eta_m + r_\eta \int_0^t e^{\alpha_\eta (s-t)} \lambda_\eta ds\\
&= e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\eta_m + \lambda_\eta r_\eta \frac{\left(1-e^{-\alpha_\eta t}\right)}{\alpha_\eta}\\
&= e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\left(\eta_m + \frac{\lambda_\eta r_\eta}{\alpha_\eta}\right)
\end{aligned} \tag{E.1}
$$

$$
\begin{aligned}
VAR\left[\eta_t\right] &= VAR\left[e^{-\alpha_\eta t}\eta_0 + \left(1-e^{-\alpha_\eta t}\right)\eta_m \right.\\
&\quad \left. +\sigma_\eta \int_0^t e^{\alpha_\eta (s-t)} dW_{\eta s} + r_\eta \int_0^t e^{\alpha_\eta (s-t)} dN_s\right]\\
&= VAR\left[\sigma_\eta \int_0^t e^{\alpha_\eta (s-t)} dW_{\eta s}\right] + VAR\left[r_\eta \int_0^t e^{\alpha_\eta (s-t)} dN_s\right]\\
&= \sigma_\eta^2 \int_0^t e^{2\alpha_\eta (s-t)} VAR\left[dW_{\eta s}\right] + r_\eta^2 \int_0^t e^{2\alpha_\eta (s-t)} VAR\left[dN_s\right]\\
&= \sigma_\eta^2 \int_0^t e^{2\alpha_\eta (s-t)} ds + r_\eta^2 \int_0^t e^{2\alpha_\eta (s-t)} \lambda_\eta ds\\
&= \left(1-e^{-2\alpha_\eta t}\right)\frac{\lambda_\eta r_\eta^2 + \sigma_\eta^2}{2\alpha_\eta}
\end{aligned} \tag{E.2}
$$

Appendix F

Derivation of Production Profit Loss In Initial Training

A team receives an initial training right before they are sent to serve in a new generation. Employees in the team do not take the previous responsibility during the training, which may lead to a production profit loss.

A team allocated to the current generation is assumed as coming from the previous generation. Figure F.1 illustrates the relation between the time index of the current generation, t, and the time index of the previous generation τ. Let t_i indicate the end

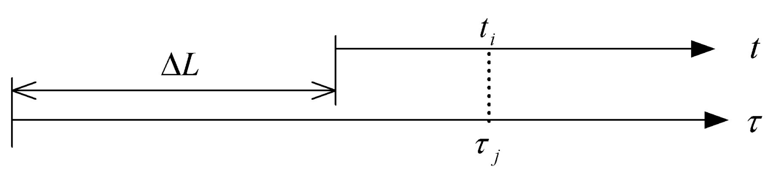


Fig. F.1. The Time Indices of Two Successive Generations

of the ith steps in the current PLC, τ_j denote the jth steps in the previous PLC, and they actually represent the same time. The current generation starts ΔL later than the previous generation, so τ_j can be estimated using Equation (F.1).

$$\tau_j = t_i + \Delta L \tag{F.1}$$

The derivation of the production profit loss in the initial training is in an assumed scenario in below. The KW-capacity for problem solving at τ_j in the previous generation is $\tilde{x}_{pj}$, and the production scale is $\tilde{x}_{wj}$. Thus, yield of the previous generation is evaluated in Equation (F.2), wherein $\lambda_{\tilde{y}}$ is the rate of yield improvement in the previous generation.

$$\tilde{y}_j = 1 - e^{-\lambda_{\tilde{y}} \frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}} \tag{F.2}$$

However, $x(\geq 0)$ teams in the previous generation is requested to receive the initial training at τ_j to prepare for serving the current generation. This causes a change in $\tilde{x}_{pj}$, denoted as $\Delta\tilde{x}_{pj}$, and x is approximately equals $-\Delta\tilde{x}_{pj}$. Thus, $\tilde{y}_j$ is lowered correspondingly, and the change in $\tilde{y}_j$ is calculated in Equation (F.3)

$$\begin{aligned} \Delta\tilde{y}_j &= \left(1 - e^{-\lambda_{\tilde{y}} \frac{\tilde{x}_{pj}-x}{\tilde{x}_{wj}}}\right) - \left(1 - e^{-\lambda_{\tilde{y}} \frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}}\right) = e^{-\lambda_{\tilde{y}} \frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}} - e^{-\lambda_{\tilde{y}} \frac{\tilde{x}_{pj}-x}{\tilde{x}_{wj}}} \\ &= -e^{-\lambda_{\tilde{y}} \frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}} \left(e^{\lambda_{\tilde{y}} \frac{x}{\tilde{x}_{wj}}} - 1\right) \end{aligned} \tag{F.3}$$

The output change of the previous generation at τ_j is obtained by scaling $\Delta\tilde{y}_j$ with $\tilde{x}_{wj}\tilde{N}_{IC}$ ($\tilde{N}_{IC}$ is the number of chips resided in a wafer in the previous generation), as indicated in Equation (F.4).

$$\Delta\tilde{O}_j = -\tilde{x}_{wj}\tilde{N}_{IC} e^{-\lambda_{\tilde{y}} \frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}} \left(e^{\lambda_{\tilde{y}} \frac{x}{\tilde{x}_{wj}}} - 1\right) \tag{F.4}$$

The production profit loss due to the initial training thus is attained, as illustrated in Equation (F.5).

$$\begin{aligned} \Delta\tilde{v}_j &= \tilde{p}_j\tilde{O}_j = \tilde{p}_j\tilde{x}_{wj}\tilde{N}_{IC}e^{-\lambda_{\tilde{y}}\frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}}\left(e^{\lambda_{\tilde{y}}\frac{x}{\tilde{x}_{wj}}}-1\right) \\ &= \tilde{a}_{1j}^{IP}\exp\left(\tilde{a}_{2j}^{IP}x-1\right) \end{aligned} \tag{F.5}$$

$\tilde{p}_j$in Equation (F.5) represents the sales price of the previous generation at τ_j.

$\tilde{a}_{1j}^{IP}$ in Equation (F.5) varies over time because it is not only a function of time but contains two time varying variables, $\tilde{x}_{wj}$ and $\tilde{x}_{pj}$. $\tilde{a}_{1j}^{IP}$ can be simplified based on two notions. First, when the current generation is introduced, yield of the previous generation has a large chance to have reached a relatively stable level $E[\tilde{y}]$. $\exp\left(-\lambda_{\tilde{y}}\frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}\right)$ thus is approximated as a constant, $1-E[\tilde{y}]$. Second, $\tilde{x}_{wj}$ can be estimated based on $\tilde{D}_j$, the demand for the previous generation of product at τ_j. That is, $\tilde{x}_{wj}$ is approximated by $\frac{\tilde{D}_j}{\tilde{N}_{IC}\tilde{y}_j}$, respectively. Although $\tilde{D}_j$ and $\tilde{y}_j$ are stochastic, they can be replaced by the expected values, $E[\tilde{D}_j]$ and $E[\tilde{y}]$. The replacements are reasonable since, when the current generation is introduced, the previous generation soon becomes a secondary product. Thus, the stochasticity in the previous generation is not a major concern in development of the current generation. The replacement substantially simplifies the problem without severely impairing the solution accuracy. Procedures for simplifying $\tilde{a}_{1j}^{IP}$ are illustrated in Equation (F.6).

$$\begin{aligned} \tilde{a}_{1j}^{IP} &= \tilde{p}_j\tilde{x}_{wj}\tilde{N}_{IC}e^{-\lambda_{\tilde{y}}\frac{\tilde{x}_{pj}}{\tilde{x}_{wj}}} = \tilde{p}_j\frac{\tilde{D}_j}{\tilde{N}_{IC}\tilde{y}_j}\tilde{N}_{IC}\left(1-\tilde{y}_j\right) \\ &= \tilde{p}_j\frac{E[\tilde{D}_j]}{\tilde{N}_{IC}E[\tilde{y}]}\tilde{N}_{IC}\left(1-E[\tilde{y}]\right) = \tilde{p}_jE[\tilde{D}_j]\left(\frac{1}{E[\tilde{y}]}-1\right) \end{aligned} \tag{F.6}$$

Similarly, $\tilde{a}_{1j}^{IP}$ is simplified in Equation (F.7).

$$\tilde{a}_{2j}^{IP} = \frac{\lambda_{\tilde{y}}}{\tilde{x}_{wj}} = \frac{\lambda_{\tilde{y}}}{\frac{\tilde{D}_j}{\tilde{N}_{IC}\tilde{y}_j}} = \frac{\lambda_{\tilde{y}}\tilde{N}_{IC}E\left[\tilde{y}_j\right]}{E\left[\tilde{D}_j\right]} \tag{F.7}$$

The production profit loss in Equation (F.5) is evaluated under the time index of the previous generation. To obtain the formulation under the time index of the current generation, as illustrated in Equation (F.8), a_{1j}^{IP} and a_{2j}^{IP} have to be transfered to a_{1i}^{IP} and a_{2i}^{IP} via Equation (F.1).

$$\Delta v_j = a_{1i}^{IP}\left(\exp\left(a_{2i}^{IP}x\right) - 1\right) \tag{F.8}$$

a_{1i}^{IP} and a_{2i}^{IP} are obtained in Equations (F.9) and (F.10), respectively.

$$a_{1i}^{IP} = \tilde{p}_{\Delta L}\tilde{D}_{\Delta L}\left(\frac{1}{E[\tilde{y}]} - 1\right)e^{-\left(\frac{\tilde{\beta}^2}{\tilde{T}_m^2}\Delta L + 0.5\tilde{\sigma}^2 + \lambda_{\tilde{p}} - \frac{\tilde{\beta}^2}{\tilde{T}_m}\right)t_i - \frac{\tilde{\beta}^2}{2\tilde{T}_m}t_i^2} \tag{F.9}$$

$$a_{2i}^{IP} = \frac{\lambda_{\tilde{y}}\tilde{N}_{IC}E[\tilde{y}]}{\tilde{D}_{\Delta L}\exp\left(-\left(\frac{\tilde{\beta}^2}{\tilde{T}_m^2}\Delta L + 0.5\tilde{\sigma}^2 - \frac{\tilde{\beta}^2}{\tilde{T}_m}\right)t_i - \frac{\tilde{\beta}^2}{2\tilde{T}_m}t_i^2\right)} \tag{F.10}$$

$\tilde{D}_{\Delta L}$ and $\tilde{p}_{\Delta L}$ in Equations (F.9) and (F.10) are the demand and the sales price of the previous generation when the current generation starts. $\tilde{\beta}$, $\tilde{T}_m$, $\lambda_{\tilde{p}}$, and $\tilde{\sigma}$ are model parameters of the previous generation.

Appendix G

Formulating Optimization with Single Decision Variable

The optimization of KWA on lattice B_i ($\forall i \in I$) has two decision variables, the KW-capacity $c_{i_{k+1}}$ and the production scale x_{wi_k} ($\forall k \in K_i$). However, it can be formulated as an optimization with single decision variable $c_{i_{k+1}}$. Let $W = \{0, 1, \ldots, U_W\}$ represent the finite integer set which consists of all possible values of x_{wi_k}, and $R_{+W} = [0, U_W]$ represent the closed set defined on R. Let all possible values of $c_{i_{k+1}}$ form a finite integer set $C = \{0, 1, \ldots, U_C\}$. $f^Z : (W \times C) \to R$ is the periodic profit function, which is denoted as $f : (R_{+W} \times C) \to R$ if assuming $x_{wi} \in R_{+W}$. f is used in formulation of the optimization with single decision variable because it makes the mathematical derivation easy. However, results based on f can be inherited by f^Z.

The periodic output function at t_{i_k}, simply denoted as O_{i_k}, is calculated in Equation (G.1).

$$O\left(c_{i_{k+1}}, x_{wi_k} | c_{i_k}, D_{i_k}\right) = N_{IC} x_{wi_k} \left(1 - e^{-\lambda_y \frac{c_{i_k} - \eta_{i_k} \min\left(c_{i_k}, c_{i_{k+1}}\right)}{x_{wi_k}}}\right) \tag{G.1}$$

Accordingly, the periodic profit function f at t_{i_k} is obtained in (G.2).

$$\begin{aligned} f\left(c_{i_{k+1}}, x_{wi_k} | c_{i_k}, D_{i_k}\right) =& p_{t_{i_k}} \min\left(D_{i_k}, O_{i_k}\right) - c_v x_{wi_k} - C^{IP}\left(c_{i_{k+1} | c_{i_k}}\right) \\ & - C^{IT}\left(c_{i_{k+1} | c_{i_k}}\right) - C^{CT}\left(c_{i_{k+1} | c_{i_k}}\right) \end{aligned} \tag{G.2}$$

If f is proven as a concave function on R_{+W}, $x^*_{wi_k}$ exists in R_{+W} and it is a function of $c_{i_{k+1}}$. The optimization of KWA whereby turns to have just one decision variable.

Equation (G.2) shows that f is not smooth on R_{+W}. Let R^A_{+W} be the subset of R_{+W} when $D_{i_k} \geq O_{i_k}$, and R^B_{+W} be the subset of R_{+W} when $D_{i_k} \leq O_{i_k}$. So, $R^A_{+W} \cup R^B_{+W} = R_{+W}$, and $R^A_{+W} \cap R^B_{+W} = 0$. The concavity of f is examined on the complements of R_{+W}, R^A_{+W} and R^B_{+W}, separately.

When $D_{i_k} \geq O_{i_k}$, the first and second order partial derivatives of f w.r.t. x_{wi_k} are illustrated in Equation (G.3) and (G.4), respectively.

$$\begin{aligned} \frac{\partial f}{\partial x_{wi_k}} = & - c_v + p_{t_{i_k}} N_{IC} \left(1 - e^{-\lambda_y \frac{c_{i_k} - \eta_{i_k} \min\left(c_{i_k}, c_{i_{k+1}}\right)}{x_{wi_k}}} \right) \\ & - e^{-\lambda_y \frac{c_{i_k} - \eta_{i_k} \min\left(c_{i_k}, c_{i_{k+1}}\right)}{x_{wi_k}}} \frac{p_{t_{i_k}} N_{IC} \lambda_y \left(c_{i_k} - \eta_{i_k} \min\left(c_{i_k}, c_{i_{k+1}}\right)\right)}{x_{wi_k}} \end{aligned} \tag{G.3}$$

$$\frac{\partial^2 f}{\partial x^2_{wi_k}} = -e^{-\lambda_y \frac{c_{i_k} - \eta_{i_k} \min\left(c_{i_k}, c_{i_{k+1}}\right)}{x_{wi_k}}} \frac{p_{t_{i_k}} N_{IC} \left(\lambda_y \left(c_{i_k} - \eta_{i_k} \min\left(c_{i_k}, c_{i_{k+1}}\right)\right)\right)^2}{x^3_{wi_k}} \tag{G.4}$$

Equations (G.3) and (G.4) indicate f is a twice-differentiable function on R^A_{+W}, and the second order partial derivative of f w.r.t. x_{wi_k} is negative, so f is concave on R^A_{+W}. When $D_{i_k} \leq O_{i_k}$, the first and second partial derivatives of f w.r.t. x_{wi_k} are illustrated in Equation (G.5) and (G.6), respectively.

$$\frac{\partial f}{\partial x_{wi_k}} = -c_v \tag{G.5}$$

$$\frac{\partial f}{\partial x_{wi_k}} = 0 \tag{G.6}$$

f is a linear functionon R^B_{+W} according to Equations (G.3) and (G.4), so f is concave on R^B_{+W}. f on R_{+W} is the minimum of two concave functions, which is still concave. The concavity of f on R_{+W} is justified.

A concave function must have a local maximum, which is a global maximum too. Thus, $x^*_{wi_k}$ exists on R_{+W} such that $f\left(c_{i_{k+1}}, x^*_{wi_k}|c_{i_k}, D_{i_k}\right) \geq f\left(c_{i_{k+1}}, x_{wi_k}|c_{i_k}, D_{i_k}\right)$. Accordingly, $x^*_{wi_k}$ is a function of $c_{i_{k+1}}$, as indicated in Equation (G.7).

$$x^*_{wi_k} = g(c_{i_{k+1}}) \tag{G.7}$$

The valuation function in Equation (3.31) is maximized by $c^*_{i_{k+1}}$ and $x^*_{wi_k}$ together, as illustrated in Equation (G.8).

$$\begin{aligned} V^*(c_{i_{k+1}}, x_{wi_k}|c_{i_k}, D_{i_k}) &= V(c^*_{i_{k+1}}, x^*_{wi_k}|c_{i_k}, D_{i_k}) \\ &= \max_{c_{i_{k+1}} \in C, x_{wi_k} \in R_{+W}} V(c_{i_{k+1}}, x_{wi_k}|c_{i_k}, D_{i_k}) \end{aligned} \tag{G.8}$$

$c^*_{i_{k+1}}$ pushes V to $V^*(c_{i_{k+1}}, x_{wi_k}|c_{i_k}, D_{i_k})$ through maximizing $V(c_{i_{k+1}}, g(c_{i_{k+1}})|c_{i_k}, D_{i_k}))$, as illustrated in Equation (G.9).

$$\begin{aligned} V^*(c_{i_{k+1}}, x_{wi_k}|c_{i_k}, D_{i_k}) = V(c^*_{i_{k+1}}, x^*_{wi_k}|c_{i_k}, D_{i_k}) &= V(c^*_{i_{k+1}}, g(c^*_{i_{k+1}})|c_{i_k}, D_{i_k}) \\ &= \max_{c_{i_{k+1}} \in C} V(c_{i_{k+1}}, g(c_{i_{k+1}})|c_{i_k}, D_{i_k}) \end{aligned} \tag{G.9}$$

f^Z is a subset of f since it is the discrete concave function corresponding to f. f^Z whereby is concave on W, and it inherits abovementioned properties of f. Thus,

$x^*_{wi_k} \in W$ exists on W such that $f^Z\left(c_{i_{k+1}}, x^*_{wi_k} | c_{i_k}, D_{i_k}\right) \geq f^Z\left(c_{i_{k+1}}, x_{wi_k} | c_{i_k}, D_{i_k}\right)$. The relation $x^*_{wi_k} = g^Z(c_{i_{k+1}})$ is obtained, accordingly. Thus, the optimization of can be formulated as having single decision variable $c_{i_{k+1}}$.

Appendix H

Approximation of Poisson Process as Binomial Process

Poisson Process, N_t, accounts the number of jumps happening in $[0, t)$. If this interval is divided into l steps in length of $\Delta T'$, the number of jumps in the kth step (i.e., $[t_{k-1}, t_k)$), X_k, is calculated in Equation (H.1).

$$X_k = N_{t_k} - N_{t_{k-1}} \tag{H.1}$$

Equation (H.1) indicates that N_t is the sum of X_k ($\forall k = 1, 2, \ldots, l$), as illustrated in Equation (H.2).

$$N_t = \sum_{k=1}^{l} X_k \tag{H.2}$$

Thus, X_k satisfies Equation (H.3).

$$P\left(X_i = x\right) = \begin{cases} 1 - \lambda_\eta \Delta T + 0(\Delta T) & x = 0 \\ \lambda_\eta \Delta T + 0(\Delta T) & x = 1 \\ 0(\Delta T) & x > 1 \end{cases} \tag{H.3}$$

Equation (H.3) indicates that X_k approximates to the Binomial variable Z in Equation (H.4) if $\Delta T'$ is small.

$$Z = \begin{cases} 1 \quad w.p.t. \quad \lambda_\eta \Delta T \\ \\ 0 \quad w.p.t. \quad 1 - \lambda_\eta \Delta T \end{cases} \tag{H.4}$$

z_k represents the outcome of Z at the kth step, then $\sum_{i=1}^{l} z_k$ has a Binomial distribution, as indicated in Equation (H.5).

$$P\left\{\sum_{k=1}^{l} z_k = n\right\} = C_n^l \left(\lambda_\eta \Delta T\right)^n \left(1 - \lambda_\eta \Delta T\right)^{l-n} \quad n = 0, 1, \ldots, l \tag{H.5}$$

It is well known that

$$\lim_{l\to\infty} P\left\{\sum_{k=1}^{l} z_k = n\right\} = \frac{e^{-\lambda_\eta t}\left(\lambda_\eta t\right)^n}{n!}. \quad n = 0, 1, \ldots \tag{H.6}$$

Equation (H.6) indicates, when $\frac{\Delta T'}{t}$ is small enough, Binomial process is a reasonable discrete approximation of Poisson process.

Appendix I

Justifying The Design of Group-Based Hybrid Tree

Infinite sequence $S_\infty(\omega) = \left\{\omega, \omega^2, \ldots\right\}$ converges to zero asymptotically since $0 \leq \omega = e^{-\alpha_\eta \Delta T'} < 1$. That is, a small positive real value δ_L and a large positive integer N_L exist such that $|\omega^{n_L} - 0| < \delta_L$ for any $n_L > N_L$. Moreover, $S_\infty(\omega)$ converges to zero at a decreasing speed. Thus, a small positive real value δ_T and a large positive integer N_T exist such that $|\omega^{n_T+1} - \omega^{n_T}| < \delta_T$ for any $n_T \geq N_T$.

A sequence $S_{N_D}(\omega) = \left\{\omega, \omega^2, \ldots, \omega^{N_D}\right\}$ is used to construct a N_D-steps binomial tree for approximating η_t ($\forall t \in [0, T]$). If the number of steps that the binomial tree have is large enough (e.g., $0 < N_T \leq N_L \leq N_D$), $S_{N_D}(\omega)$ acts in a manner similar to $S_\infty(\omega)$. Thus, $\overrightarrow{\omega}_l$ can be reasonably approximated by $\overrightarrow{\omega_{hl}}$ in Equation (I.1).

$$\overrightarrow{\omega_{hl}} = \begin{cases} \left[\omega^l, \omega^{l-1}, \ldots, \omega\right] & 1 \leq l \leq N_T \\ \left[\underbrace{\overline{\omega}^l_{N_T}, \ldots, \overline{\omega}^l_{N_T}}_{l-N_T}, \omega^{N_T}, \ldots, \omega\right] & N_T < l \leq N_L \\ \left[\underbrace{0, \ldots, 0}_{l-N_L}, \underbrace{\overline{\omega}^{N_L}_{N_T}, \ldots, \overline{\omega}^{N_L}_{N_T}}_{N_L-N_T}, \omega^{N_T}, \ldots, \omega\right] & N_L < l \leq N_D \end{cases} \tag{I.1}$$

$\overline{\omega}^l_{N_T}$ in Equation (I.1) is the average of ω^k ($N_T + 1 \leq k \leq l$), as indicated in Equation (I.2).

$$\overline{\omega}^l_{N_T} = \frac{1}{l - N_T} \sum_{k=N_T+1}^{l} \omega^k \tag{I.2}$$

The error of approximation $\overrightarrow{\omega}_l$ with $\overrightarrow{\omega}_{hl}$ is finite. Equation (I.3) gives the boundary of the error when it is measured as Manhattan distance (i.e., 1-norm distance in the Euclidean space R^l).

$$||\overrightarrow{z_l} \cdot \overrightarrow{\omega_{hl}} - \overrightarrow{z_l} \cdot \overrightarrow{\omega}_l||_1 \leq \begin{cases} 0 & 1 \leq l \leq N_T \\ (l - N_T)\,\delta_T & N_T < l \leq N_L \\ (l - N_L)\,\delta_L + (N_L - N_T)\,\delta_T & N_L < l \leq N_D \end{cases} \tag{I.3}$$

A hybrid tree is built based on the approximation of $\overrightarrow{\omega}_i$ with $\overrightarrow{\omega}_{hi}$ in Equation (I.1). Equation (I.1) indicates that the hybrid tree in the first N_T steps is a binomial tree. From step $N_T + 1$ to distinguish the slight differences among ω^k ($\forall k = N_T + 1, N_T + 2, \ldots, l$) is not a necessity. Thus, from step $N_T + 1$ to N_L the hybrid tree has a lattice-like structure (i.e., some tree nodes are combined, but the number of unique nodes is still growing). After step N_L ω^l is so small such that it can be treated as zero. Thus, since step $N_L + 1$ the hybrid tree has a strip structure (i.e., some tree nodes are combined, and meanwhile, the tree stops generating now nodes).

The replacement of $\overrightarrow{\omega}_l$ by $\overrightarrow{\omega_{hl}}$ leads to a slight reduction in the mean and the variance of η_t, as indicated in Equations (I.4) and (I.5).

$$\Delta E\left[\eta_{t_l}\right] = r_\eta E\left[\overrightarrow{z}_l \cdot (\overrightarrow{\omega}_l - \overrightarrow{\omega_{hl}})\right] \leq \begin{cases} 0 & 0 < l \leq N_L \\ (l - N_L)\delta_T r_\eta \lambda_\eta \Delta T' & N_L < l \leq N_D \end{cases} \tag{I.4}$$

Equation (I.4) shows that the error of $E[\eta_t]$ is zero before t_{N_L}, and increases linearly after then at a speed of $\delta_T r_\eta \lambda_\eta \Delta T'$. Thus, the error of $E[\eta_t]$ can be lowered through delaying the strip phase or through reducing the step size of hybrid tree.

$$
\Delta VAR\left[\eta_{t_l}\right] = r_\eta^2 VAR\left[\overrightarrow{z}_l \cdot (\overrightarrow{\omega}_l - \overrightarrow{\omega_{hl}})\right]
$$

$$
\leq \begin{cases} 0 & 0 < l \leq N_T \\ r_\eta^2 \lambda_\eta \Delta T' \left(1 - \lambda_\eta \Delta T'\right) \frac{(l-N_T-1)\delta_T^2}{2} & N_T < l \leq N_L \\ r_\eta^2 \lambda_\eta \Delta T' \left(1 - \lambda_\eta \Delta T'\right) \left(\frac{(N_L-N_T-1)}{2}\delta_T^2 + (l - N_L)\,\delta_L^2\right) & N_L < i \leq N_D \end{cases} \tag{I.5}
$$

Equation (I.5) shows that the error of $VAR[\eta_t]$ is zero till t_{N_T}, increases linearly between $(t_{N_T}, t_{N_L}]$ at a speed of $0.5 r_\eta^2 \lambda_\eta \Delta T' \left(1 - \lambda_\eta \Delta T'\right) \delta_T^2$, and still increases linearly after t_{N_L} yet at a speed of $r_\eta^2 \lambda_\eta \Delta T' \left(1 - \lambda_\eta \Delta T'\right) \delta_L^2$. Thus, the error of $VAR[\eta_t]$ can be reduced through delay the lattice-like phase and the strip phase, or through reducing the step size of hybrid tree.

Appendix J

Derivation of Demand Model Sensitivity

The demand model in Equation (3.4) contains four parameters: σ, M, D_0 and T_m. Demand is varied by the change in any of the four parameter. $\%\Delta D_t(\cdot)$, the relative change in demand w.r.t. each of the parameters, identify the demand model sensitivity.

The formulation of demand change caused by a change in σ is obtained directly by taking the difference between the two values of demand, as indicated in Equation (J.1).

$$\Delta D_t = D_0 e^{\int_0^t \mu_s ds - \frac{1}{2}(\sigma+\Delta\sigma)^2 t + (\sigma+\Delta\sigma)W_t} - D_t = D_t \left(e^{-\frac{1}{2}\sigma^2 t\left(2\frac{\Delta\sigma}{\sigma}+1\right)+\sigma W_t\left(\frac{\Delta\sigma}{\sigma}\right)} - 1 \right) \quad \text{(J.1)}$$

Multiplying both sides of Equation (J.1) with $\frac{1}{D_t}$ yields the expression of $\%\Delta D_t(\sigma)$, as illustrated in Equation (4.1).

The formulation of demand change caused by a change in any other three parameters, however, can not be obtained in the same way as attaining $\%\Delta D_t(\sigma)$. The reason is that M, D_0 and T_m are parameters in the implicit function of β, as indicated in Equation (B.7). Thus, the formulation of $\%\Delta D_t(\cdot)$ w.r.t. each of the three parameters is derived through Taylor expansion.

$f(\beta)$ is a function of β, as illustrated in Equation (J.2). it is the portion that contains β in the implicit function of β.

$$f(\beta) = \beta \exp\left(-\frac{\beta^2}{2}\right) \tag{J.2}$$

Equation (B.7) indicates that β is a function of M, D_0 and T_m. Thus, the partial derivatives of D_t with respect to M, to D_0, and to T_m can be obtained using Equations (J.3-J.5), respectively.

$$\frac{\partial D_t}{\partial M} = \frac{\partial D_t}{\partial \beta}\frac{d\beta}{df(\beta)}\frac{\partial f(\beta)}{\partial M} \tag{J.3}$$

$$\frac{\partial D_t}{\partial D_0} = \frac{D_t}{D_0} + \frac{\partial D_t}{\partial \beta}\frac{d\beta}{df(\beta)}\frac{\partial f(\beta)}{\partial D_0} \tag{J.4}$$

$$\frac{\partial D_t}{\partial T_m} = D_t\beta^2\left(-\frac{t}{T_m^2} + \frac{t^2}{T_m^3}\right) + \frac{\partial D_t}{\partial \beta}\frac{d\beta}{df(\beta)}\frac{\partial f(\beta)}{\partial T_m} \tag{J.5}$$

Equations (J.3-J.5) indicates that $\frac{\partial D_t}{\partial \beta}$, $\frac{d\beta}{df(\beta)}$, $\frac{\partial f(\beta)}{\partial M}$, $\frac{\partial f(\beta)}{\partial D_0}$ and $\frac{\partial f(\beta)}{\partial T_m}$ have to be found to obtain the expressions of $\%\Delta D_t(\cdot)$.

First, according to Equation (3.4), the partial derivative of D_t w.r.t. β is obtained in Equation (J.6).

$$\frac{\partial D_t}{\partial \beta} = D_t\beta\frac{t}{T_m}\left(2 - \frac{t}{T_m}\right) \tag{J.6}$$

Second, whether $\frac{d\beta}{df(\beta)}$ exists should be examined. $f(\beta)$ is differentiable on R, and Equation (J.7) gives the derivative of $f(\beta)$ on R.

$$\frac{df(\beta)}{d\beta} = \left(1 - \beta^2\right)e^{-\frac{\beta^2}{2}}. \tag{J.7}$$

Equation (J.7) indicates that $f(\beta)$ is a monotonic decreasing function on $[1, \infty)$. β in the demand model is around 3 which is in this range, so the inverse function of $f(\beta)$, $f(\beta)^{-1}$, is differentiable for all $f(\beta)$ defined on $[1, \infty)$, and

$$\frac{d\beta}{df(\beta)} = \frac{df^{-1}(\beta)}{df(\beta)} = \frac{1}{\frac{df(\beta)}{\beta}} = \frac{1}{1-\beta^2} e^{\frac{\beta^2}{2}}. \tag{J.8}$$

Third, based on Equation (B.7), the partial derivatives of $f(\beta)$ with respect to M, to D_0, and to T_m are obtained as in Equations (J.9-J.11).

$$\frac{\partial f(\beta)}{\partial M} = \frac{D_0 \sqrt{2\pi} T_m}{-M^2} \tag{J.9}$$

$$\frac{\partial f(\beta)}{\partial D_0} = \frac{\sqrt{2\pi} T_m}{M} \tag{J.10}$$

$$\frac{\partial f(\beta)}{\partial T_m} = \frac{D_0 \sqrt{2\pi}}{M} \tag{J.11}$$

By plugging Equations(J.6), (J.8), (J.9), (J.10), and (J.11) into Equations (J.12-J.14), the first order partial derivatives of D_t with respected to M, to D_0, and to T_m are obtained in Equations (J.12-J.14), respectively.

$$\frac{\partial D_t}{\partial M} = \frac{D_t}{M} \frac{\beta^2}{\beta^2 - 1} \frac{t}{T_m} \left(2 - \frac{t}{T_m}\right) \tag{J.12}$$

$$\frac{\partial D_t}{\partial D_0} = \frac{D_t}{D_0} \frac{\beta^2}{1 - \beta^2} \left(2 + \frac{t}{T_m}\left(2 - \frac{t}{T_m}\right)\right) \tag{J.13}$$

$$\frac{\partial D_t}{\partial T_m} = \frac{D_t}{T_m} \frac{\beta^2}{\beta^2 - 1} \frac{t}{T_m} \left(\beta^2 \left(\frac{t}{T_m} - 1\right) - 1\right) \tag{J.14}$$

From the first order partial derivatives of D_t in Equations (J.12-J.14), the high order partial derivatives of D_t with respect to M, to D_0, and to T_m are obtained in Equations (J.15-J.17).

$$\frac{\partial^i D_t}{\partial M^i} = \frac{D_t}{M^i} \prod_{j=0}^{i-1} \left(\frac{\beta^2}{\beta^2 - 1} \frac{t}{T_m} \left(2 - \frac{t}{T_m} \right) - j \right) \tag{J.15}$$

$$\frac{\partial^i D_t}{\partial {D_0}^i} = \frac{D_t}{{D_0}^i} \prod_{j=0}^{i-1} \left(\frac{\beta^2}{1 - \beta^2} \left(2 + \frac{t}{T_m} \left(2 - \frac{t}{T_m} \right) \right) - j \right) \tag{J.16}$$

$$\frac{\partial^i D_t}{\partial {T_m}^i} = \frac{D_t}{{T_m}^i} \prod_{j=0}^{i-1} \left(\frac{\beta^2}{\beta^2 - 1} \frac{t}{T_m} \left(\beta^2 \left(\frac{t}{T_m} - 1 \right) - 1 \right) - j \right) \tag{J.17}$$

Provided with any order partial derivative of D_t wth respect to M, to D_0, and to T_m, Taylor expansion gives the formulation of $\%\Delta D_t(\cdot)$, as illustrated in Equations (4.4), (4.3), and (4.2).

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Vita

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