A real options framework for platform-based product family design

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**A REAL OPTIONS FRAMEWORK FOR PLATFORM-
BASED PRODUCT FAMILY DESIGN**

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**A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
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ABSTRACT

Product family design and platform-based product development have been well recognized as an effective means to achieve mass customization. Investing into product families which build on platforms and shared modules, installs flexibility for a company to accommodate future customization requirements, while taking a risk due to increased complexity in design and production. It is crucial to properly identify and capitalize on favorable and worthwhile opportunities of future investments while mitigating the possible losses from adverse market development. Accordingly, the fundamental research issue of justifying the relative economic value of product families and platforms is addressed.

The general gist of existing approaches coincides with the traditional principle of capital budgeting that is based on discounted cash flows (DCF) analysis. The DCF-based methods imply management's passive commitment to a single operating strategy, which ignores the strategic value inherent in flexibility under an uncertain marketplace. Considering numerous options associated with product family design, the DCF approach tends to underestimate the upside potentials to a design project from management flexibility. In this regard, this research employs a real options theoretic approach whereby platform-based product family design is modeled as an investment strategy being crafted by a series of real options that are continuously exercised to achieve expected returns on investment.

In this research, a hybrid real options valuation framework is proposed to recognize the value of flexibility both inherent in a product family design project and built in the product platform. Two types of real options are identified for product family design, namely product-related and project-related options, in order to integrate engineering analysis and financial analysis into a coherent framework. In addition, a numerical options pricing method is proposed to derive analytical solutions for the hybrid valuation model that is formulated as multivariate partial differential equations. Coupled with a simulation approach to solve the combinatorial optimization problem associated with product family design, a hybrid genetic algorithm is developed in accordance with the hybrid real options valuation framework.

The real options valuation framework is further extended to tackle the flexibility planning problem of product platforms. Tradeoff studies between payoffs from appropriate platform flexibility levels and diversity of customer needs are set up to shed light on the strategic decision-making involved in the product platform flexibility planning along with uncertainties in product demands and the market. To demonstrate the feasibility and potential of the real options theoretic approach, case studies in a vibration motor manufacturer are also reported.

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Singapore, 7th September 2007

Ching Moi (Vicky), LIM

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NOMENCLATURE

μ	Average of estimated cycle time	CRR	Cox,Ross, and Rubiustein
σ	Standard deviation of estimated cycle time		lattice approach
Θ	Pre-defined threshold	CS	Customer satisfaction
Ψ	Payoff	ΔD	Design changes
A	Armature	DA	Design alternative
A^F	Price of PFD	DEs	Differentiation enablers
AA	Analytic approximations	DM	Design module
B	Bracket	DCF	Discounted cash flows
BEG	Boyle, Evnine, and Gibbs lattice approach	DPs	Design parameters
BOM	Bill-of-materials	DSM	Design structure matrix
C^F	Cost estimate of financial options	EC	Encoding
C^T	Cost estimate of technical option	EFDS	Explicit finite difference schemes
CAPM	Capital asset pricing model	F	Frame
CBs	Common bases	ΔF	Customized functional features
CMs	Configuration mechanisms	F^L	Lower bounds of functional feature value
CNs	Customer needs	F^U	Upper bounds of functional feature value
COAPA	Compound-option analytic polynomial approximation	FAM	Flexibility analysis methodology
		FRs	Functional requirements

GA	Genetic algorithm	OM	Optimization model
GBM	Geometric Brownian motion	OEM	Options encapsulation method
GBOM	Generic bill-of-materials	ΔP	Process variations
GOM	Generic optimization model	PcP	Process platform
GRG	Generalized Reduced Gradients	PdP	Product platform
HGA	Hybrid Generic Algorithm	PDE	Partial differential equation
I	Instantiation	PE	Process efficiency
I	Information content	PFA	Product family architecture
IFDS	Implicit finite difference schemes	PFD	Product family design
LA	Lattice Approach	PP	Potential payoff
LTBM	Log-transformed binomial method	PpP	Product portfolio
M	Magnet	PVs	Process variables
MCS	Monte-Carlo simulation	QA	Quadratic approximation
MFD	Modular function deployment	QFD	Quality function deployment
MLTBL	Multidimensional log- transformed binomial lattice method	r	Risk-free rate
M	Market	RH	Rubber holder
MS	Market segment	RO	Real options
NEK	Niklas Ekvall lattice approach	SBLM	Std. binomial lattice approach
NI	Numerical Integration	SLP	Sequential linear programming
NLP	Non-linear programming	SOR	Successive over relaxation
NPV	Net present value	SP	Stochastic processes
		SQP	Sequential quadratic programming
		T	Expiration date
		$U(\Delta F)$	Customer perceived value

USL	Upper specification limit	$x^{Lau}(\bullet)$	Launch option
VPSHA	Various problem-specific heuristic approximation	$x^{NEST}(\bullet)$	Nesting option
W	Weight	$x^{PROC}(\bullet)$	Producing option
$x^{Aba}(\bullet)$	Abandon option	$x^{REMO}(\bullet)$	Removing option
$x^{ATTa}(\bullet)$	Attaching option	$x^{SCAL}(\bullet)$	Scaling option
$x^{CONF}(\bullet)$	Configuring option	$x^{SCRN}(\bullet)$	Screening option
$x^{Def}(\bullet)$	Defer option	$x^{SWAP}(\bullet)$	Swapping option
x^F	Financial value of real options	$x^{Swi}(\bullet)$	Switch option
		x^T	Technical value of real options

CHAPTER 1:

INTRODUCTION

This chapter introduces the motivation and general background leading to this research. The rationale and challenges of mass customization are discussed. Accordingly, the problem area is identified, along with the strategy for solution, as well as the objectives and scope of this research. Also outlined is a holistic view of the technological roadmap for this research.

1.1 BACKGROUND

Manufacturing companies have devoted much attention to the contemporary battlefield called mass customization, which aims to satisfy individual customer needs by introducing product proliferation while taking advantage of mass production efficiency (Pine, 1993). To compete in such a marketplace, manufacturers have been attempting to expand their product lines and diversify their product offerings with the intuitively-appealing belief that large product variety may stimulate sales and generate additional revenue (Ho and Tang, 1998). Initially variety does improve sales as the offerings become more attractive; but as variety keeps increasing, the law of diminishing returns suggests that the benefits do not keep pace (Wortmann *et al.*, 1997). Facing such a dilemma, companies are geared towards the optimization of their external variety with respect to the internal complexity resulting from product differentiation (Tseng and Jiao, 1996).

Towards this end, designing and developing product families have been well recognized as an effective means to achieve both economies of scale and scope in order to accommodate diverse customer needs across different market niches (Meyer and Utterback, 1993; Robertson and Ulrich, 1998; Sundgren, 1999). In addition to leveraging the cost of delivering an increasing product variety by reusing proven elements in a firm's activities and offerings, product family design (PFD) offers a multitude of benefits including reduction in development risks and system complexity, improved ability to upgrade products, and enhanced flexibility and responsiveness of manufacturing processes (Sawhney, 1998). Furthermore, platform-based product development has extended the traditional boundaries of product development by tackling from an even broader perspective which encompasses business strategy, marketing, manufacturing and production, customer engineering, information technology, and general management.

Many companies have invested in PFD practice where product variety are fulfilled based upon common product platforms to satisfy diverse markets while maintaining the economies of scale and scope within their manufacturing capabilities (Robertson and Ulrich, 1998). Such a highly irreversible investment, for a company, is expected to have a long-term service effort to product proliferation and complexity of product fulfillment. However, designing a product family under a mass customization environment often involves great uncertainty, where the realization of payoffs and strategic adaptability in relation to technology investments (product platform) may differ from what management has expected at the outset. Investing in PFD and product platforms is therefore undertaken as a high risk and irreversible commitment to a company. It is crucial to properly identify and capitalize on favorable and worthwhile

opportunities of future investments while mitigating the possible losses from adverse market development.

1.2 RESEARCH PROBLEM AND MOTIVATIONS

According to the reasoning above, it is surprising to know that professional managers make the decisions on PFD practice based on their *a priori* belief. Precisely, how cost-effective the PFD is under platform-based product development, how adaptable and valued the invested platforms are to adverse and future market development, and what are the possible opportunities from engineering and business perspectives along project life cycle?

Such fundamental hindrances lie on a lack of scientific ground to justify these research questions. Many studies are devoted to either PFD configuration, product families modeling, product family decision support systems, or product family evaluation metrics. The problem is, that there is not yet a unified framework for valuation, decision support, and strategic planning of platform-based PFD development which coexist with both business and engineering concerns.

(1) *Economic valuation and methodology.* There is a lack of economic justification of PFD under platform-based product development. It is rather limited as compared to those justifying economically to manufacturing and production for product families. Most of the existing valuation frameworks learnt from the comprehensive review in Chapter 2, coincide with the principle of traditional capital budgeting, namely DCF-based approach. The primary drawback of the traditional capital budgeting principle is that it tends to underestimate the upside value of an investment.

(2) *Decision support and strategic planning.* An adequate decisions support and strategic planning framework is needed due to the failures of current proposed

frameworks in deriving financial-engineering decisions, as well as, defining possible future opportunities of platform investments under PFD strategic planning.

Therefore, the main purpose of this dissertation is to fulfill these imperatives as well as to tackle the underlying fundamental rationale, configuration mechanism of PFD, and strategic planning of platforms.

1.3 RESEARCH OBJECTIVES AND SCOPES

The primary objective of this research is to develop a valuation framework for PFD under platform-based product development. Focusing on the aforementioned motivations, the strategy for solution of this research is to value PFD under platform-based product development using a real options theoretical approach. Real options approach is adopted as it overcomes the common pitfalls associated with traditional capital budgeting. Further details are presented in Section 2.6.3.

Accordingly, the research scope is identified as the following:

(1) Satisfying diverse customer demands is the ultimate goal of PFD under mass customization. Customer needs are reckoned to vary from time to time, which also implies the quality, price, sales, and economic attractiveness of a PFD. According to Amram *et al.* (1999), an investment with greater risk may provide a greater opportunity for creating value. In this case, PFD itself may be regarded as an investment. To capture the effectiveness (flexibility) of a PFD, a valuation methodology must be able to model various uncertainties. In this case, real options approach proves its powerful mechanism in justifying for the embedded flexibility value of PFD while dissolving the uncertainties from the flexibility premiums derived. Therefore, a financial analysis framework for PFD using real options approach is developed, which involves the following tasks:

- Investigate the close analogies between real options thinking and PFD and reveal important valuation properties;
 - Analyze sources of uncertainties related to PFD and formulate appropriate distribution process to characterize the nature of these uncertainties;
 - Identify the real options relevant to product platforms in accordance with the PFD configuration process;
 - Develop a systematic pricing model and formulate a PFD valuation framework based on real options financial analysis; and
 - Develop a numerical method to solve the PFD valuation model with consistency, stability, and efficiency.
- (2) PFD decision-making involves primarily the tradeoff between customer-perceived variety offered by the product families and complexity of product fulfillment resulting from product differentiation. PFD thus suggests itself as an optimization problem with the objective to maximize the economic value of product offering. The linchpin of PFD optimization is to facilitate the choice of the best design alternative with respect to diverse customer demands and markets. Therefore, a hybrid valuation framework is developed for PFD optimization which involves the following tasks:
- Understand the technical and financial aspects of PFD;
 - Differentiate real options in terms of both technical and financial aspects and determine appropriate valuation parameters for each of the categories;
 - Formulate a comprehensive PFD optimization model with consideration of both technical and financial achievements; and
 - Develop an efficient method to solve the PFD optimization problem.

- (3) The economic attractiveness of PFD originates from managerial flexibility inherent in product platforms to deal with various uncertainties. In a real situation, decision makers often have difficulties in stating a priori to what extent the product platform is favorable to call or put. Therefore, capturing flexibility and potential values of product platforms are significant in PFD valuation. It is even challenging to setup the guidelines for product platforms planning through analyzing the tradeoffs among customer needs' uncertainty, flexibility of product platforms, and potential value of PFD. Therefore, the PFD valuation framework is applied to analyze the product platform flexibility planning tradeoffs, which involve the following tasks:
- Identify the characteristics and tradeoffs involved in product platform strategic decisions; and
 - Develop a product platform flexibility planning model based on the real options framework.
- (4) Verify the PFD valuation framework and product platform flexibility planning model by developing case studies.

1.4 ORGANIZATION OF THIS DISSERTATION

Figure 1-1 presents a holistic view of the technological roadmap that reveals the coherence of this research. Different aspects of the research framework are tackled by individual chapters.

Chapter 2 is devoted to a review of the state-of-art research regarding PFD and platform-based product development. Common consensus and key issues are systematically reviewed, including such concepts as product family, product platform, product architecture, product variety, modularity and commonality, product portfolio, and process platform. Also reviewed are product family modeling and decision support,

process variety management, as well as process platform and production configuration. In particular, the cutting-edge product family evaluation metrics and methodologies are analyzed thoroughly. Based on the review, the problem area and research opportunities are identified.

In Chapter 3, a real options framework is developed for financial analysis of PFD. With analogy to the real options thinking, the real options and valuation parameters are identified for PFD. A pricing model is also formulated in accordance with the PFD context. A case study of vibration motor family design is developed to validate the framework.

Chapter 4 reports a numerical options pricing approach to PFD valuation. Multidimensional log-transformed binomial lattice (MLTBL) method is developed by taking into account the issues of transformation and jump size and probabilities selection. The performance of the MLTBL method is studied in terms of consistency, stability, and efficiency.

In Chapter 5, PFD optimization is modeled from two dimensions: the design artifact and design process. Accordingly, a hybrid valuation framework is developed to appraise PFD in terms of both engineering and financial perspectives. The product- and project-related options are identified and modeled in regard to PFD. A pricing model that involves such parameters as product demand, payoff, and cost is formulated. A case study of vibration motors is reported to unveil the feasibility and potential of the hybrid valuation framework.

To solve the hybrid PFD optimization model, a hybrid genetic algorithm (GA) is developed in Chapter 6. Discussed in details are the associated features of the solution framework such as configuration space formulation, generic encoding, initialization, configuration constraints handling, fitness evaluation, selection and reproduction,

crossover, mutation, and termination. An implementation of the hybrid GA for searching the optimum of PFD among all configurations from existing real options portfolio is demonstrated. In addition, the performance of the GA is analyzed through sensitivity and efficiency analyses.

In Chapter 7, a flexibility planning model based on real options is developed for the economic justification of platform-based product development. The flexibility planning model employs customer-perceived utility measure to parameterize customer demand uncertainty. Experiments are designed to reveal tradeoffs of potential payoff and flexibility levels under uncertainty. A case study is also developed to illustrate how the planning model can be applied to reveal the economic attractiveness of flexible platform strategies for designing vibration motor families.

In the last chapter, the achievements in addressing the research objectives are summarized. A critical evaluation of the dissertation is summarized, along with recommendations for future research.

Figure 1-1: Organization of the dissertation

CHAPTER 2:

LITERATURE REVIEW

Product family design and platform-based product development have received much attention in both academia and industries alike over the last decade. Platform-based product development essentially entails a conceptual structure and overall logical organization of generating a family of products by providing a generic umbrella to capture and utilize commonality, within which each new product is instantiated and extended so as to anchor future designs to a common product line structure, as shown in Figure 2-1.

Figure 2-1: The principle of platform-based product development for mass

customization (Jiao and Tseng, 1999)

The rationale lies in not only unburdening the knowledge base from keeping variant forms of the same solution, but also in modeling the design process of an entire class of products that can widely variegate designs based on individually customized requirements within a coherent framework (Jiao and Tseng, 1999).

Figure 2-2 illustrates the decision framework of platform-based product development along the entire spectrum of product realization according to the concept of design domains (Suh, 2001). Based on such a holistic view, platform-based product development encompasses consecutively four domains, namely the customer, functional, physical, and process domains. Product family decision-making involves a series of “what-how” mappings between these domains.

Figure 2-2: A holistic view of platform-based product development (Suh, 2001)

The customer domain is characterized by a set of customer needs (CNs) representing segmentation of markets that demand for product families and triggering downstream platform-based product development mappings in a cascading manner. The CNs are first translated into functional requirements (FRs) in the functional domain, in which designers take into account engineering concerns and elaborate these requirements based on available product technologies. The mapping between the customer and functional domains constitutes the front-end issues associated with developing product families. Such a product family definition task is always carried out within an existing product portfolio and manifests itself through those common

practices of order configuration and sales force automation. Platform-based product development solutions are generated in the physical domain by mapping FRs to design parameters (DPs) based on the shared product platform. This stage involves typical decisions regarding product family design and configuration. At the front-end, the product portfolio articulates detailed achievement of customer satisfaction in the customer domain in the form of specifications of functionality in the functional domain. On the other hand, the main focus of platform-based product development is the technical feasibility of DPs in terms of fulfilling the specified functionality.

The back-end issue associated with product families involves the process domains, which is characterized by process variables (PVs). The mapping from DPs to PVs entails the process design task, which must generate manufacturing and production planning within existing process capabilities and utilize repetitions in tooling, setup, equipment, routings, and so on. Corresponding to a product platform, production processes can be organized as a process platform in the form of standard routings, thus facilitating production configuration for diverse product family solutions (Jiao *et al.*, 2000a). Since the main concern in the process domain is manufacturability and cost commitment, process design is the *de facto* enabler of mass production efficiency.

As a result, the achievement of platform-based product development essentially depends on the justification of cost-effectiveness around three pillars: the customer perceived value, design changes, and process variations, that is,

$$\Delta F \leftarrow \Gamma(U(\Delta F), \Delta D, \Delta P) \text{ for all customization requirements,} \quad (2-1)$$

where ΔF denotes the customized functional features, $U(\Delta F)$ indicates the customer perceived value, ΔD characterizes the design changes, and ΔP indicates the process variations.

Throughout the mappings across the domains, a comprehensive background review of the state-of-art research in product family design is presented in this chapter. The review reveals the fundamental issues related to product family decision, including scalable product family design, configurable product family design, product family modeling, product family decision support systems, and product family evaluation metrics. Accordingly, the problem area, and the strategy for solution are identified. The logical flow of the relevant issues, problem area, and strategy for solution is given in Figure 2.5.

2.1 PRODUCT FAMILY DESIGN

Corresponding to the scalable and modular product platforms, there are two types of approaches to platform-based product family design. One common approach is called scalable (namely parametric) product family design, whereby scaling variables are used to “stretch” or “shrink” the product platform in one or more dimensions to satisfy a variety of customer needs (Simpson *et al.*, 2001a). The other approach is referred to as configurational product family design, which aims to develop a modular product platform, from which product family members are derived by adding, substituting, and/or removing one or more functional modules (Ulrich, 1995; Du *et al.*, 2001).

2.1.1 Scalable Product Family Design

The scalable approach was first proposed by Simpson *et al.* (2001a). They introduce a product platform concept exploration method based on robust design principles by minimizing the sensitivity of performance variations in scaling factors. Messac *et al.* (2002a) integrate physical programming into the product platform concept exploration method to increase its effectiveness. Fellini *et al.* (2002) consider commonality as a

constraint in PFD. Nayak *et al.* (2002) incorporate the platform selection problem into the commonality and performance trade-off procedure by maximizing commonality at the product family level while satisfying the design requirements of each individual product. Messac *et al.* (2002b) introduce a product family penalty function to the selection of right combination of common and scaling variables, where those design variables causing more performance loss are identified as scaling factors. Fellini *et al.* (2004) employ sensitivity analysis to derive the penalty on performance loss due to commonality. In the context of designing a family of aircraft, Willcox and Wakayama (2003) apply multidisciplinary optimization to gain insight into the effect of design variable scaling across multiple aircraft that carry different missions yet share common parts.

Scalable PFD involves two basic tasks (Simpson, 2004). The first one is platform selection – to determine which design parameters that take common values. While many existing methods assume that the platform architecture is known *a priori* (Fujita *et al.*, 1999), some approaches determine platform variables along with scalable variables during optimization (Akundi *et al.*, 2005; Dai and Scott, 2004). The subsequent task is to determine the optimal values of common and distinctive variables by satisfying performance and economic requirements. Most approaches consider only a single product platform, where each platform variable is shared across the entire product family. This strategy excels in computational simplicity; but may lead to a situation that some low-end products may be over-designed and certain high-end products may be under-designed (Dai and Scott, 2004). The other strategy is to consider multiple product platforms in PFD, such that design variables can be shared by any subset of product variants within the product family (de Weck *et al.*, 2003).

Multiple-platform design enhances exploration of the solution space, whereas sacrificing the computational efficiency (Seepersad *et al.*, 2002).

Simpson (2004) reviews optimization algorithms widely used for PFD. Linear and non-linear programming algorithms, such as sequential linear programming (SLP), sequential quadratic programming (SQP), non-linear programming (NLP), and generalized reduced gradients (GRG), are employed in many studies, in addition to derivative-free methods including genetic algorithms, simulated annealing, pattern search, and branch and bound techniques. Some specific algorithms and heuristics are also available for use depending upon particular solution frameworks, including decision-based design (Li and Azarm, 2002), target cascading (Kokkolaras *et al.*, 2002), 0-1 integer programming (Fujita *et al.*, 1999), physical programming (Messac *et al.*, 2002a), and the compromise decision support problem (Simpson *et al.*, 2001a). When the design space is small, exhaustive search techniques (Hernandez *et al.*, 2001) or orthogonal arrays (Blackenfelt, 2000a) are always adopted to enumerate various combinations of parameter settings. In practice, most problems involve a large number of options, which constitute a typical combinatorial optimization problem. As a result, genetic algorithms are most advocated to tackle the combinatorial nature of PFD problems (Simpson, 2004).

2.1.2 Configurational Product Family Design

The configurational approach to product family design is also frequently called module-based product family design (Simpson, 2004). It is based on the development of modular product architectures. As defined by Ulrich and Tung (1991), a modular product architecture involves one-to-one mappings from functional elements in the function structure to the physical components of a product, where decoupled interfaces between components can be specified. Ulrich (1995) points out that the modular

product architecture allows each functional element of the product to be changed independently by changing only the corresponding component. This is advantageous to produce custom-built products from standard models. It also makes standardization possible, which is essential to achieve the economy of scale; therefore, using modular product architectures, variety can be created by configuring existing building blocks. Salient issues regarding configurational PFD include module identification, interface standardization, and architecture embodiment as discussed next.

(1) *Module identification.* Erlandsson *et al.* (1992) develop a method with three major steps that help to identify product modules. In their method, the right product specification is attained by adopting quality function deployment (QFD). Module creation, interface analysis and module configuration are carried out through creating different modular structures according to the QFD matrix (i.e., the house of quality). Erixon and Ostgren (1993) extend this method by applying the QFD matrix to modular analysis and coin it as modular function deployment (MFD) with focus on the evaluation of module integration.

Yu *et al.* (2003) apply the DSM as a tool to identify highly interactive groups of product elements and to cluster them into modules. Hölttä and Salonen (2003) compare three modularization methods using commercial products. They reveal that the MFD method is the least repeatable, whereas the computerized DSM method is the most repeatable, and the heuristic approach falls in between. Malmström and Malmqvist (1998) integrate the DSM and MFD methods to tackle both technical and economical aspects in the early stages of product architecture development. Stone *et al.* (2000) formulate a set of heuristics for grouping functions to form a module. Hölttä *et al.* (2003) developed a five-step algorithm of grouping and creating a dendrogram for finding common modules across products for platforming a product family. Salhieh and

Kamrani (1999) employ a clustering technique for identifying design modules. Otto *et al.* (2000) propose a framework for architecting a family of products that share interchangeable modules. They define a modularity matrix for one family of products from a manufacturer, allowing commonalities to be easily identified. Gershenson *et al.* (2003) provide an extensive comparison of several DSM-based methods for identifying modular architectures.

(2) *Interface standardization.* The importance of standardized interfaces in product architectures is recognized by Meyer and Lehnerd (1997). Sanderson and Uzumeri (1995) suggest that the product family evolution may have been restricted if clear and robust physical interfaces are not developed and defined carefully. Sanchez (1994) discusses the need for distinct and standardized interfaces between the vital parts of the product family. Sundgren (1999) explores the concept of interface management in new product platform development. Blackenfelt (2000b) studies robust design of interfaces in order to increase interface commonality among a variety of products. Ulrich and Eppinger (1995) point out that product architecting is tantamount to interface definition.

Martin and Ishii (2002) introduce a coupling index to assess the amount of coupling between modular interfaces to facilitate product family planning for multiple generations. Sosa *et al.* (2004) identify the distinction among interfaces from the energy, material, spatial and informational aspects. Hillstrom (1994) proposes a method that helps the designer clarify how interfaces between modules influence module functions and how to select the best interface location. Mikkola and Gassmann (2003) introduce a modularization function for analyzing the degree of modularity in a given product architecture by taking into account the number of components, number of interfaces and substitutability factor of a given product architecture. Van Wie *et al.* (2001)

address the embodiment issues of module interfaces in terms of the connections between modules.

(3) *Architecture embodiment*. Newcomb *et al.* (1996) investigate the methods of reasoning about sets of product architectures and how to perform configuration design of modular products. Kamrani and Gonzalez (2003) discuss design for modularity using a genetic algorithm-based method. Tatikonda (1999) studies the planning and execution of different types of projects within a product family platform series. Gonzalez-Zugasti *et al.* (2000) formulate platform-based PFD as a general optimization problem considering the constraints of individual product variants and constraints of the family as a whole. Agard and Kusiak (2004) apply data mining techniques to PFD with emphasis on mapping specific functional requirements to a technical structure. Yigit *et al.* (2002) optimize modular products as a generalized subset selection problem subject to a balance of the quality loss due to modularization and the cost of reconfiguration. Chandrasekaran *et al.* (2004) propose a template approach to product platform-based design based on prior product design knowledge and the flow and conversion of energy through a product. Kurtadikar and Stone (2003) use high level customer needs alone to define the product's base platform and differentiating modules during the conceptual design stage of product development and thus plan a product family before considering any architecture. Robertson and Ulrich (1998) articulate three tools for supporting platform planning: product plan, differentiation plan, and commonality plan.

2.1.3 Product Family Modeling

Baldwin and Clark (2000) develop a discipline-independent data model to provide constructs for modeling products with optional contents. Felfernig *et al.* (2001) apply the unified modeling language to the modeling of configuration knowledge bases for mass customizable products. The initiative of Product Family Classification Tree

emphasizes the classification of end-products and/or modules from a functional viewpoint (Bei and MacCallum, 1995). To facilitate representations from multiple perspectives, Generic Product Modeling is advocated to represent product families from both commercial and assembly views (Wortmann *et al.*, 1997). McKay *et al.* (1991) describe product families from both sales/customer and assembly views by incorporating descriptions of detailed product data into specifications of product variety. Siddique and Rosen (1999) develop a graph grammar approach to product platform design. Du *et al.* (2002a) apply graph grammars to product family modeling. A graph rewriting system is developed to support product family configuration design (Du *et al.*, 2002b). Set-based model is an attempt to the formal representation of product platform design and manufacturing processes (Finch, 1999). Männistö (2000) studies the conceptual modeling of product families, with particular emphasis on the problems related to the evolution of product family descriptions and the product individuals created according to them.

Van Wie *et al.* (2003) consider product architecture representation as organizing a deluge of information in terms of both function and form. To model product family configuration, Zhang *et al.* (2005) propose to organize and manage product knowledge through a knowledge component that includes configuration rules and constraints. Bohm and Stone (2004) investigate the representation of functionality for supporting reuse. Sharman and Yassine (2004) study some forms of abstraction for describing product architectures, including DSM, molecular diagrams, and visibility-dependency signature diagrams. Costa and Young (2001) introduce a product range model (i.e., product families) for information modeling of variant and adaptive design. Tiihonen *et al.* (1998) develop a method of managing and modeling a product family as a configurable product, which is based on the conceptualization of components, attributes,

resources, ports, contexts, functions and constraints. Jiao *et al.* (1998) observe different data types underlying product families that involve product-to-product, product-to-family, and family-to-family relationships. To characterize variety and its derivation, Jiao *et al.* (2000) propose a generic variety structure consisting of common product structures, variety parameters, and configuration constraints.

Shooter *et al.* (2005) develop an information management infrastructure for product family planning and platform customization. Corbett and Rosen (2004) develop computational methods for modeling and combining multiple design spaces so that product family configurations can be identified while satisfying all constraints. To articulate design of modular product architectures, Rosen (1996) considers three design spaces in terms of material compatibility, connections, and covers. Schwarze (1996) studies the fundamental problems of configuring multiple-variant products with emphasis on configuration information modeling. Johannesson (1992) attempts to build computer-based parametric product family models. Computer supported product platform models are proposed by Claesson *et al.* (2001). The work of Sivard (2000) emanates from axiomatic design and the ISO standard STEP AP214 with the purpose of improving computer representation of information that concerns product families and product platforms. Johannesson and Claesson (2005) report a combined function-means and parametric modeling approach to product platform design. Their concepts are being deployed by Saab Automobile as the next logical evolution of product description systems.

2.1.4 Product Family Decision Support Systems

Kusiak and Huang (1996) and O'Grady and Liang (1998) put forth design with modules that centers around module selection. Liang and O'Grady (2000) focus on a particular design environment where modules may be available from one or more

geographically dispersed sources, and where data concerning the modules may be in a multitude of databases scattered across the globe. Huang and Liang (2001) develop formalism for design with modules, such that customer requirements are met using modules from suppliers geographically separated through diverse computer platforms.

Siddique and Rosen (2001) develop a product family configuration reasoning system to identify common platforms from a collection of similar existing products, as well as to generate product families from these common platforms. Siddique and Boddu (2004) propose an information framework of integrating customers into configuration design using a graph grammar and templates for modules. Zha *et al.* (2004) examine the development of a knowledge-intensive support scheme and a comprehensive fuzzy clustering and ranking methodology for product family design evaluation. Forza and Salvador (2002) investigate how product configuration systems support the order acquisition and fulfillment process in a high product variety environment. Huang (2004) develops an agent-based knowledge management system for decision support of modular product collaborative design.

Online product configurators have recently received much attention to enable customers to interactively specify and adapt a product according to their individual preferences (Sabin and Weigel, 1998). Bramham and MacCarthy (2003) examine the empirical evidence of available configurators in terms of matching configurator attributes against business strategies. Hvam (2004) reviews the design and implementation of product configuration systems from the viewpoint of industrial applications. Simpson *et al.* (2003) investigate the frameworks for web-based platform customization. Common configuration systems for product families necessitate product specific knowledge and often overstrain customers (Blecker *et al.*, 2004a). Advisory systems are thus advocated to guide customers according to their profile and

requirements through a personalized configuration process ending with the generation of product variants that better fulfill the real customer needs (Blecker *et al.*, 2004b). Blecker *et al.* (2004a) present a multi-agent based design for the configuration process of product variety. Ardissono *et al.* (2003) report on an EU-funded project, CAWICOMS Workbench, which aims at next generation web-based applications that support distributed configuration of products and services within a supply chain.

2.2 PRODUCT FAMILY EVALUATION METRICS

Product family design essentially entails a type of multi-objective optimization problems (Simpson *et al.*, 2005). In many cases, such multiple criteria decision-making, given a number of alternatives at different levels of abstraction of the product architecture, requires to leverage on three pillars: cost, revenue, and performance. In addition, it needs to weigh the revenue from product cannibalization by commonality with respect to the cost savings from commonality (Robertson and Ulrich, 1998).

2.2.1 Technical Metrics

(1) *Commonality*. Kota *et al.* (2000) develop a measure that captures the level of commonality in a product family. With application to automotive underbodies, Siddique *et al.* (1998) propose to measure component commonality and connection commonality in order to capture characteristics of platform commonality and product variety. Maupin and Stauffer (2000) take into account simplicity, direct costs, and delayed differentiation for commonality metrics. Thoteman and Brandeau (2000) present an approach for determining the optimal level of commonality in a sub-product that does not differentiate models from the customer's point of view. Emphasizing on component sharing, Ramdas *et al.* (2003) present a methodology for determining which version of a set of related components should be offered to optimally support a defined

finished product portfolio. In the work of Fellini *et al.* (2002), an optimal design problem is formulated as the maximization of commonality by choosing the product components to be shared without exceeding a user-specified performance loss tolerance and subject to different levels of performance losses. McAdams and Wood (2002) develop a quantitative metric for design-by-analogy based on the functional similarity of products. Thevenot and Simpson (2005) compare various commonality indices for assessing product families, including the Degree of Commonality Index (Collier, 1981), Total Constant Commonality Index (Wacker and Trelevan, 1986), Product Line Commonality Index (Kota *et al.*, 2000), Percent Commonality Index (Siddique *et al.*, 1998), Commonality Index (Martin and Ishii, 1997), and Component Part Commonality Index (Jiao and Tseng, 2000).

(2) *Modularity*. Prasad (1998) studies the product and process complexity associated with design for variety, highlighting the importance of determining the right amount of decomposition. To quantify such a granularity paradox, a measure of communication effort is introduced in order to achieve an optimal balance. Gershenson *et al.* (2003) develop a measure of relative modularity for modular product design. Mikkola and Gassmann (2003) assume that the degree of modularity in a given product architecture is constrained by the composition of its components. Allen and Carlson-Skalak (1998) introduce some measures of modularity for conceptual design. Ulrich (1995) simply defines the function-to-component ratio for each product as one modularity metric. Hölttä and Salonen (2003) propose a measure of modularity based on singular value decomposition of the binary DSM. Guo and Gershenson (2004) develop a metric to measure product modularity using a component-to-component connectivity matrix. Siddique and Rosen (2001) account for both functional and form

issues in their partitioning method that involves combinatorics. Stone *et al.* (2000) develop product family and customer needs ratings for modules.

(3) *Distinctiveness*. Martin and Ishii (1997) quantify the costs of providing variety in order to quantitatively guide designers in developing products that incur minimum variety costs. Through commonality analysis, van Wie *et al.* (2006) study how differences between platform elements and differentiating elements are evidenced in the product layout or configuration. Simpson and D'Souza (2004) introduce a genetic algorithm-based approach to product family design that balances the commonality of the products in the family with the individual performance (i.e., distinctiveness) of each product in the family. A Product Variety Index is proposed by Simpson *et al.* (2001b) to help resolve this tradeoff. Dobrescu and Reich (2003) propose a variety index and a standardization index that resemble the commonality indices of Martin and Ishii (2002).

(4) *Platform-related metric*. Meyer and Lehnerd (1997) develop two platform related measures, named platform efficiency and platform effectiveness, for evaluating the performance of product families. Focusing on the generational aspect of product platforms, Martin and Ishii (2002) develop two indices, called Generational Variety Index and Coupling Index, to measure a product's architecture. Dahamus *et al.* (2000) propose to architect a portfolio of products by exploiting commonality and reusing modules across the family of products, rather than a fixed product platform upon which derivative products are created. That is, the platform itself allows for several possible sizes and types. Fellini *et al.* (2004) introduce a metric, called Sharing Penalty Vector, to the optimal selection of product platforms for family products with mild variation. Messac *et al.* (2003b) introduce a Product Family Penalty Function to promote platform commonality during product family optimization. De Weck *et al.* (2003) adopt a market segment model using the sales volume, the price and the competing product alternatives

for product family and platform portfolio optimization. Jiao and Tseng (2004) develop a design customizability index and a process customizability index for evaluating the cost effectiveness of a design to be customized in order to meet individual customer needs. Zha *et al.* (2004) introduce two metrics, market efficiency and investment efficiency, to the evaluation and selection of product design for mass customization.

2.2.2 Financial Metrics

(1) *Profit/Economic Value.* Numerous methods dealing with optimal design use various objectives originated from the profit or expected revenue (Fujita and Yoshida, 2004; Nelson *et al.*, 2001). Many studies have revealed that such a profit measure based on the dollar value is unrealistic in most cases (Tarasewich and Nair, 2001). As such, researchers have been developing various instruments to improve the measurement of profit performance. Balakrishnan and Jacob (1996) introduce share of choices as the objective. Chen *et al.* (2002) try to maximize performance ratings of design concepts while minimizing functional coupling and coupling of design concepts with respect to constraints. Michalek *et al.* (2005) formulate the evaluation problem as profit maximization by minimizing the technical performance deviation. De Weck *et al.* (2003) propose to optimize product platform design by maximizing overall product family profitability and reducing the development time and cost. Jiao and Zhang (2005) combine the consumer surplus with the producer surplus based on the customer-perceived value of design.

Typical approaches to estimate costs and values coincide with the traditional principle of capital budgeting that is based on discounted cash flows (DCF) analysis. When dealing with numerous options associated with product family design, the DCF approach tends to underestimate the upside potentials to a design project from management flexibility (Kogut and Kulatilaka, 1994). Real options have been applied

to value specific aspects of product development, such as design modularity (Baldwin and Clark, 2000). Otto *et al.* (2003) explore the real options concept for determining proper levels of independent product architectural attributes. Jiao *et al.* (2005a) apply a real options framework to flexibility valuation of a product family architecture. Banerjee and de Weck (2004) propose a flexible product option valuation framework to evaluate the conditions where a flexible architecture is no longer financially viable *vis-à-vis* fixed architectures. The rationale of combining technological and business decisions in real options valuation for optimal design decisions is supported by Georgiopoulos *et al.* (2002). Jiao *et al.* (2005a) propose a hybrid real options model considering the value of flexibility either inherent in a product family design project or that can be built in product platforms.

(2) *Cost*. Kim and Chhajed (2001) develop an economic model that considers a market consisting of a high segment and a low segment. They determine that large commonality decreases production costs but makes the products more indistinguishable from one another, which makes the product more desirable for the low segment but less desirable for the high segment. Fisher *et al.* (1999) present an analytic model of component sharing based on empirical testing of varying practice of component sharing for automotive braking systems. Fujita and Yoshida (2004) develop a monotonic cost model for the assessment of benefits of commonality. Gonzalez-Zugasti *et al.* (2000) propose a methodology to design product platforms and variants with consideration of technical performance requirements and product family costs.

Fixson (2005) outlines a roadmap for product architecture costing from a product life cycle perspective. Park and Simpson (2005) examine the effects of commonality decisions on individual costs based on activity-based costing. To link modularity and cost, Fixson (2002) develops a multi-dimensional product architecture description

method that considers the level of function-component allocation, interface intensity, interface reversibility, and interface standardization. Siddique and Repphun (2001) assess the cost implications of product architectural decisions when product architectures allow sharing of parts, modules, or components of a product across product families. The savings from the reuse of designs influence both development cost and time (Siddique, 2001). To design robust product families and determine product platform extent, Hernandez *et al.* (2001) estimate production time, the material cost, and the inventory cost by modeling manufacturing issues as functions of design variables. Martin and Ishii (1997) employ a setup cost index as a surrogate for indirect cost associated with product variety.

Table 2.1 shows the detailed summary of some influential papers on product family design justification. Eventually, this has driven to explain the problem areas of this research given in the following section.

Table 2-1: Current State of Research on Product Family Design Justification

Author (year)	Formulation Details					Product Family Modeling Approach	Product Family Decision Support Systems	Notes
	Scalable PFD	Configurable PFD	Technical Metrics	Financial Metrics	Uncertainty			
Fellini et al. (2002,2004)	x		Commonality (Sharing Penalty Vector)	Not address explicitly		Mixed-discrete Programming	First Order Taylor Series Approximation	- Approximation remains reasonably accurate with the condition that individual optimal design not lie large distance away from each other
Georgiopoulos et al. (2002)				Profit	Product Demand & Market Share		DCF Analysis-based Methods	- Valuate the back-end process of PFD using CAPM
Gonzalez-Zugasti et al. (2000)		x	Technical Performance Requirements	Product Family Cost	Uncertainties During Development & Operation of Products	Not Specified	Decision Analysis Tools Coupled with RO Concept	- Consider the delayed design & abandon options for platform flexibility planning - Discount for sharing common platform is applied - Technical metrics of PFD are not address explicitly
Henderson & Clark (1990)					Technology		Conceptual Framework	- Focus on conceptual analysis
Jiao et al. (2005a)		x	Technical Value	Payoff Value	Customer Needs	PFA	Hybrid RO, MLTBL Approach, GA	- Optimize PFD by maximizing its ultimate goal : flexibility value - Analyze long-term strategic planning of platforms investment
Li & Azarm (2002)				Profit & Market Share	Customer Preference, Market Size, Product Cost, Price, Discount Rate		DCF Analysis-based Methods, Monte Carlo Simulation	- Assume demand can be forecasted & market size is estimated, no significant reaction from the competition - Evaluation for the conventional product design

Continued

Author (year)	Formulation Details					Product Family Modeling Approach	Product Family Decision Support Systems	Notes
	Scalable PFD	Configurable PFD	Technical Metrics	Financial Metrics	Uncertainty			
Martin & Ishii (1997)		x	Modularity & Distinctiveness	Setup Cost Index				- Perform regression analysis on cost data collected from activity-based costing - Not solving PFD optimization problem
Nayak et al. (2002)	x		Commonality			Goal Programming	Variation-based Modeling	- Maximize robustness of PFD rather than encourage flexibility of PFD
Otto et al. (2000, 2003)		x	Commonality	Profit	Technology		RO Concept	- Cost & economic performance are calculated in monetary units
Sanchez (1991)				Profit	Price		RO	-Valuate product-mix manufacturing flexibility
Simpson et al. (2001a,b,2003)	x		Distinctiveness			Product Platform Concept Exploration Method & Metamodels	Web-based Platform Customization Framework	-Evaluate the performance of product platform without considering uncertainty
Stone et al. (2000)		x	Modularity			Formal Functional Decomposition & Heuristics Method		- Focus on front-end PFD process modeling rather than evaluation

2.3 PROBLEM AREAS

2.3.1 Economic Justification

Product family design and development are associated with new cost and profit structures that can be coined as “economies of scale and scope”. Current research on the economic and performance evaluation of product families is dominated by empirical studies, ad hoc samples, or broad approaches based on cost accounting. Traditional cost accounting by allocating fixed costs and variable costs across multiple products may produce distorted cost-carrying figures due to possible sunk costs associated with investment into product and process platforms (Jiao and Zhang, 2005). It is quite common in product family fulfillment that design and manufacturing admit resources, and thus the related costs, to be shared among multiple products in a reconfigurable fashion, as well as per-product fixed costs (Moore *et al.*, 1999). Yano and Dobson (1998) observe a number of industrial settings, where a wide range of products are produced with very little incremental costs per se, or very high development costs are shared across broad product families, or fixed costs and variable costs change dramatically with product variety. They point out that “the accounting systems, whether traditional or activity-based, do not support the separation of various cost elements”. Safizadeh *et al.* (2000) derive similar results from an empirical study of 142 manufacturing plants: plants that provide a high degree of customization incur high cost structures. However, when controlling for production processes the tradeoff disappears. This means once a company has defined its product range along with an appropriate production process, product family-based customization that falls into a specific range does not cost any extra.

The economic justification of product families requires the identification of proper measures and performance indicators to characterize different outcomes of a product customization system. This task is imperative because the current accounting systems are not designed for assessing the true economical benefits from the total value chain point of view. Even if the focus is shifted from cost control to value creation, existing accounting and control systems are mostly dominated by the practice of product costing. Savings and additional costs resulting from different degrees of interaction with the customers are not covered by most industrial accounting systems. Activity-based costing and the balanced score card approaches may provide initial solutions; however, approved ratios for calculating the value of customer relationships are still missing; nor are parameters for evaluating the extent of the market research information gained by aggregated customer knowledge. Moreover, the value contribution of product families should be evaluated from the customers' perspective. There is rarely attempt to explicitly measure the need for individualization or to quantify the value of product families from a customer's perspective. The issue of justifying the economic value of introducing individualized products is of vital importance. Only if the increment in the customer-perceived value or utility suffices enough can product customization become a mass phenomenon. Recent study on the valuation of flexibility has suggested that the real options approach surmounts traditional DCF analysis-based methods that tend to ignore the upside potentials from management flexibility (Otto *et al.*, 2003; Jiao *et al.*, 2005a).

2.3.2 Uncertainty

The risks related to product family development need to be addressed properly. Typical operation uncertainties dealt with in most of the current work include demand, price, environment, time duration, and technological uncertainties. Robertson and

Ulrich (1998) observe the organizational risks related to platform development. Developing product platforms in most cases requires more investments and development time than developing a single product, which may delay the time to market and influence the return on investment time. Meyer and Lehnerd (1997) point out the risks of weak common platforms, which undermine the competitiveness of the entire product line, and subsequently affect a broad array of products. In addition to fixed investments, developing platforms may result in over-design of low-end product variants in order to enable reuse with high-end products (Krishnan and Gupta, 2001). Henderson and Clark (1990) identify one potential negative effect of modular product architectures that originates from the risk of creating barriers to architectural innovation. Organizational forces may also hinder the ability to balance commonality and distinctiveness (Halman *et al.*, 2003). Price uncertainty is considered in the product development valuation by Sanchez (1991). The technology uncertainty and evolved obsolescence are treated throughout the product life cycle (Otto *et al.*, 2003; Chi *et al.*, 2001).

2.3.3 Flexibility

Most of the approaches estimate the costs and values related to a project by undergoing the Discounted Cash Flows (DCF) analysis such that the Net Present Value (NPV) is measured. The comparison of unit costs under DCF analysis has resulted in the loss of cost savings opportunities from the management flexibility (Bengtsson, 2001). The DCF-based methods assume a priori to embed a single operation, which implies management's passive commitment to a certain operating strategy. Therefore, DCF analysis usually underestimates the upside value of investment (Kogut *et al.*, 1994). In addition, the NPV approach treats projects as independent investment opportunities and accepts only those projects with positive NPV of the symmetric

probability distribution as shown in Figure 2-3a. This implies an inflexible management where irrevocable commitments to the operating strategies are made at the outset and abiding until the end of the project life (Trigeorgis, 1996). Obviously, this assumption contradicts the practical case of PFD, where flexibility to configure among different options is the key enabler for mass customization (Jiao and Tseng, 2003). Recent study on the valuation of flexibility has suggested that the real options approach surmounts traditional DCF analysis-based methods that tend to ignore the upside potentials from management flexibility, that is, the flexibility premiums value from an asymmetry probability distribution as shown in Figure 2-3b (Otto *et al.*, 2003; Jiao *et al.*, 2005a).

Figure 2-3: Characteristics of symmetry and asymmetry probability distributions

(Trigeorgis, 1996)

Jiao *et al.* (2005b) remark on the assumption made at a static point of time which may result in the unreliable and impractical decisions. Real options thinking furnishes managers to go beyond a single point estimate of the likely future and recognize a broader domain of possible opportunities (Kogut and Kulatilaka, 1994). By operating investment with options, it dissolves the uncertainties from the flexibility premiums derived. Real options evaluation thus accounts for the embedded value of flexibility in projects. Traditional valuation models exclude the consideration of any opportunity for changing investment decisions, whereas real options provide powerful mechanisms for funding the pursuit of a broader bandwidth of opportunities. Most cost-effectiveness scenarios can be considered as sets of options.

2.4 REAL OPTIONS THEORY

The real options theory applies the principles and valuation techniques of financial options to real assets (Trigeorgis, 1996). In general, two basic types of options can be distinguished, namely calls and puts. A call or put labels the option holder's right to buy or sell an underlying asset for a fixed exercise price. Options have the associated characteristics of flexibility, uncertainty, and irreversibility. Flexibility refers to very important incident for which the options holder has the right, but not the obligation, to exercise the options. Meanwhile, the element of uncertainty is also associated in options due to the economic attractiveness of the options which mainly depend on the development of the underlying asset. The irreversibility is related to the fact that the options holder's right ceases to exist once the options are exercised. In essence, options limit the downside potential of the underlying asset while at the same time offering an upside potential. As a result, options have an inherent value and investors accept to pay a price for such a options premium. This phenomenon is illustrated in Figure 2-4 which shows that the greater risk embedded in an investment is able to provide a greater option premium (Amram *et al.*, 1999). The value of an option and hence the premium are both assessed by options pricing models.

Figure 2-4: Risk versus possible investment value (Amram *et al.*, 1999)

The fact that the options theory excels in real asset applications lies in the payoff of the real options. Real options have been tailored to value specific aspects of product development, for example, design modularity (Baldwin and Clark, 2000), R&D resource allocation (Sharpe and Keelin, 1998), and awareness of the value of flexibility (Ford and Sobek, 2005). Considering the stochastic aspect of design configuration, Gonzalez-Zugasti *et al.* (2001) introduce real options concept to model the risks and benefits of delayed design decisions that incur during the product development process. The rationality of combining technological and business decisions in real options valuation for optimal design decisions is also supported by Georgiopoulos *et al.* (2002). Despite the real options approach is proven accessible over various types of flexibility valuation (Bengtsson, 2001; Trigeorgis, 1996), many of the existing valuation models are found to dominate the principles of product development and manufacturing.

2.4.1 Real Options for Manufacturing Flexibility

Manufacturing flexibility is defined as the ability to adapt to environmental uncertainty and change (Slack, 1987; Gupta and Goyal, 1989; Sethi and Sethi, 1990). In another word, only minimum penalty in time, cost, or performance is acceptable in the product mix (Upton, 1994; Van Dijk, 1995). Planning on such flexibility has received much attention from both academia and industries (Sethi and Sethi, 1990). Flexibility categories and measures have been studied extensively (for a review, see Gupta and Goyal, 1989; Sarker *et al.*, 1994). Jordan and Graves (1995) point out that the capacity and flexibility planning involve many parameters that are uncertain in long-range planning.

Gupta and Goyal (1989) and Ramasesh and Jayakumar (1991) provide the guidelines for the selection of the flexibility types and measures. The analysis of the major criteria is focused on three major aspects: (1) the competitive strategy where types of flexibility are identified and prioritized; (2) the existence of flexibility types and uncertainties in the external and internal environments; and (3) different types of

flexibility that map into different manufacturing process configurations. Other aspects, such as the functional responsibilities and the organizational position are pointed out by Slack (1987). McCutcheon *et al.* (1994) and Zipkin (2001) identify the need to assess and develop a firm's flexibility capabilities. Fogliatto *et al.* (2003) estimate the viability of mass customization systems implementation through the analysis of customization indexes based on customer requirements, supplier delivery flexibility, and production flexibility under the Quality Function Deployment (QFD) matrix.

Gerwin (1993) shows a conceptual framework of the tradeoffs between variety (diversity) and flexibility. He emphasizes the importance of strategic planning in making explicit manufacturing strategy decisions to jointly influence uncertainties in the environment and provides the appropriate level of flexibility in the production system in order to optimize the profit performance. Du *et al.* (2006) perform the tradeoffs between costs and benefits using the real options theoretical model in order to assist the justification of an appropriate flexibility level of the reconfigurable manufacturing systems in diverse environments. Suarez *et al.* (1996) study manufacturing flexibility empirically by analyzing data from 31 printed circuit board assembly plants all over the world. They find out that more automated plants are generally less flexibility, and those factors that are not directly connected with the production systems, such as worker involvement in decision making, also contribute to flexibility. They suggest six flexibility source factors to provide alternative paths to achieve four types of the first-order flexibility (i.e., mix, volume, new product, and delivery time). Upton (1994) notes that there exists a general relationship between the sources of competitiveness and the elements of flexibility. He identifies three sources of competitiveness: (1) customization; (2) quick response; and (3) broad product lines. These roughly parallel the first-order flexibility types proposed by Suarez *et al.* (1996).

de Groote (1994) also notes the relationship among the technology, flexibility planning, and competitiveness. He proposes a rigorous mathematical formulation of the general flexibility planning problem; however, the formulation is abstract and includes no operational method. Katok *et al.* (2003) develop a formal mathematical flexibility planning model showing that analytical and some commonly-used methods are generally under valuing the flexibility. They propose a sampling-based optimization algorithm for assessing the benefit of manufacturing flexibility. A manufacturing Flexibility Analysis Methodology (FAM) is proposed by Kahyaoglu *et al.* (2002), offering the insights for particular management issues, such as effectiveness of a firm's current capabilities in handling diverse circumstances, the potential flexibility opportunities for the machine operations (i.e. setup improvements), and the maximal manufacturing flexibility to be achieved under various levels of configuration attributes and environment changes.

2.4.2 Real Options for Product Development

Many literatures have contributed to real options analysis for R&D projects, for example, Dixit *et al.* (1994), Trigeorgis (1996), Gamba *et al.* (1999), Perlitz *et al.* (1999), Jacob *et al.* (2003), Worner *et al.* (2003), Blau *et al.* (2004), and McGrath *et al.* (2004), which have demonstrated the promising management techniques in technology management improvement. As a consensus, product development is viewed as an enormous irreversible investment that adheres to several issues such as the probabilities of technical success, high development expenditures, uncertain market impact, scarcity of new feasible product lines, and limited human and capital resources (Blau *et al.*, 2004). To manage these issues, the product development flexibility is served to maximize the expected returns at an acceptable level of market uncertainty and a given level of corporate resources. Although patent issue is not as much informative as other

R&D measures, it is taken into the consideration by Hall (1999) in the R&D flexibility valuation, which appears as the extra information beyond the valuation results especially for measuring the success of R&D program.

Pennings and Lint (1997) develop a sequential framework using real options approach for the R&D decision making. Huchzermeier and Loch (1999) evaluate the flexibility by introducing a distinction between the financial uncertainty and stochastic variability of the R&D operations. Cohen *et al.* (1996) and Lint and Pennings (1999) derive explicit decision rules to solve the tradeoffs between project validation and market pre-emption by taking into account uncertainties related to markets and technologies. Brach *et al.* (2001) propose a mixed diffusion jump model to allocate the generic collaborating-funding for the development of new drug based on extrinsic options value. Lint *et al.* (2001) develop a stage-gate approach to capture the flexibility value of new product development cross functionally. Lint (2002) enhances the conventional R&D resource allocation problem by integrating the scoring approach in the options valuation. The divided triangle (DIRECT) optimization algorithm and sequential quadratic programming are introduced by Georgiopoulos *et al.* (2002) to solve the capacity allocation problem under the constraint of design specifications. Jiao *et al.* (2004) design a Product Family Architecture (PFA) flexibility valuation framework to tackle the optimization of platform-based product development using the Log-transformed Binomial Method (LTBM). A nested real options is assigned by Bradhan *et al.* (2004) to value a portfolio of IT projects in a real-world setting and prioritize the projects using the ranking approach.

Griliches (1981), Cockburn *et al.* (1987), and Griliches *et al.* (1987) study the flexibility valuation of the technological assets such as R&D and patents held by a firm. Gamba *et al.* (1999) apply the projected successive over relaxation (SOR) method to

determine an optimal investment timing prior to the expiry of patent. Alvarez *et al.* (2001) explore an optimal timing for the adoption of an incumbent technology and opportunities for technology upgrade under technology uncertainty.

2.4.3 Potentials of Real Options for Product Family Design

As witnessed in this comprehensive review, the product family design and platform-based product development have been tackled from a broad scope of product fulfillment by many researchers in the past decade. With the understanding of the current research tendency for product family design and platform-based product development, problem areas are underlined in Section 2.4 as the prospects for further research efforts. In most of the existing studies, real options theory has been applied wishfully to the innovative product development whereby no references are accessible from the existing technologies or materials. In contrast, this research focuses on the product family design and platform-based product development working on an existing platform, which are also the key enablers to achieve the economy of scale and scope in mass customization. Under mass customization, customer's uncertain needs are realized to be varying from time to time, which implicitly imply the quality, price, sales, and payoff of a new product. Therefore, satisfying diverse customer demands has become the ultimate goal for product family design proliferation whereas under innovative product development, its success is determined by the realization of a new product.

Real options valuation models are scarce in current research with respect to product families. Meanwhile, most of the works are confined to the formal real options modeling framework which focuses on valuing options for specific asset properties such as value, uncertainty and discount rate, as well as options designs in terms of timing, exercise conditions, and exercise costs (Trigeorgis, 1996). Moreover, studies

have suggested many common assumptions of real options, for example, (a) future asset behavior and value must conform to well-defined processes; (b) markets are complete and arbitrage opportunities are available; (c) sources of uncertainty are few and independent; (d) payouts or other costs of delaying decisions are small; and (e) planning has one or few options (Lander and Pinches, 1998). However, these assumptions do not hold well for the product development projects (Alessandri *et al.*, 2005). Therefore, assumptions made should conform to PFD valuation.

Economic attractiveness of product family design mainly depends on the managerial flexibility of real options underlying the assets, that is, the platforms and variant modules. The upside potential of product family design can be assessed economically based on the flexibility value of configuration. Most importantly, the options involved in product family design must be conformed to the configuration process and properly identified. Typical generic real options that are found integrated in current product family design valuation framework, includes time to build (Sanchez, 1991; Lint *et al.*, 1999; Gamba *et al.*, 1999), abandon (Sanchez, 1991; Angelis, 2000; Huchzermeier *et al.*, 2001), wait (Sanchez, 1991; Sullivan *et al.*, 1997), shut down (Sanchez, 1991; Lint *et al.*, 2001), growth (Kim *et al.*, 1996; Huchzermeier *et al.*, 2001; Lint *et al.*, 2001), and exchange (Gamba *et al.*, 1999; Neely *et al.*, 2001) options.

2.5 FLEXIBILITY PLANNING

Flexibility planning has received much attention in product development and manufacturing (Sethi and Sethi, 1990). Flexibility categories and measures have been studied extensively (Gupta and Goyal, 1989; Sarker *et al.*, 1994). Jordan and Graves (1995) point out that capacity and flexibility planning involve many parameters that are uncertain in long-range planning. Gerwin (1993) shows a conceptual framework of the tradeoffs between variety or diversity and flexibility. He emphasizes the importance of

strategic planning in making explicit manufacturing strategy decisions to jointly influence uncertainties in the environment and advises the appropriate level of flexibility in the production system in order to optimize the profit performance. Suarez *et al.* (1996) study manufacturing flexibility empirically by analyzing data from 31 printed circuit board assembly plants all over the world. They find out that more automated plants are generally less flexible, and the factors that are not directly connected with the production system, such as worker involvement in decision making, also contribute to flexibility. They further suggest the six flexibility source factors and provide alternative paths to achieve the first-order flexibility types, namely mix, volume, new product, and delivery time flexibilities.

Upton (1994) notes that there exists a general relationship between the sources of competitiveness and the elements of flexibility. He identifies three sources of competitiveness, namely customization, quick response, and broad product lines. These sources roughly parallel the first-order flexibility types proposed by Suarez *et al.* (1996). de Groote (1994) also notes the relationships among the technology, flexibility planning, and competitiveness. He proposes a rigorous mathematical formulation of the general flexibility planning problem, however, the formulation is abstract and no operational method is involved. Katok *et al.* (2003) develop a formal mathematical model for flexibility planning showing that analytical and some commonly-used methods are generally under valuing the flexibility. They propose a sampling-based optimization algorithm for assessing the benefit of manufacturing flexibility. Du *et al.* (2005) develop a real options theoretical model to assist the flexibility planning in a reconfigurable manufacturing system.

Although the concepts, dimensions, and valuation frameworks of the flexibility planning have been well defined in product development and manufacturing (D'Souza

and Williams, 2000), the flexibility planning in PFD system remains unattended. Furthermore, there are no or few references to the gauge or measure of the product platform flexibility in terms of holism (Koste and Malhotra, 1999). Despite the investment costs for flexible operations being typically quantifiable, it is less common to justify the economic values of flexible product platforms as customer demand uncertainty is often disregarded by the planners (Jordan and Graves, 1995).

2.6 SUMMARY

Substantial progress has been achieved in the areas of product family design optimization, product family modeling, and product family decision support. Meanwhile, studies on the economic justification for product family design are still scarce. More specifically, the gist of platform-based product development lies in the uncertainty and flexibility issues whereby they are overlooked in the traditional capital budgeting approach such as DCF analysis. One of the strategies to solutions is real options valuation which is a theoretic approach associated with the characteristics of the flexibility, uncertainty, and irreversibility. The fundamental issues involved in product family design are illustrated in Figure 2-5.

Figure 2-5: Fundamental issues of product family design

CHAPTER 3:

REAL OPTIONS IDENTIFICATION AND VALUATION FOR FINANCIAL ANALYSIS OF PRODUCT FAMILIES

Realizing the importance of economic justification for product families, this chapter adopts the real options approach to model the product family design as an investment strategy, which is crafted by a series of continuously exercised options to achieve the expected returns on investment. In accordance with the identified real options associated with product family, a valuation framework is developed. To demonstrate the feasibility and potential of the developed framework, a case study of mobile phone vibration motor family design is reported.

3.1 REAL OPTIONS FOR PRODUCT FAMILIES

Based on the real options theory, PFD can be treated as a design project under an investment. For the most cost-effectiveness variant derivation, PFD can be referred to as design project decisions regarding a portfolio of options (investment “installments”) within the project life. By valuating PFD with the options concepts, there exists the close but not exact analogies between options concepts and PFD. Table 3-1 draws the parallel between PFD and the options concepts according to six typical factors: time period until investment opportunity disappears, uncertainty of expected cash flows, present value of expected cash flows, value lost over duration of options, risk-free interest rate, and present value of fixed costs, which influence an option value (Lander and Pinches, 1998).

Table 3-1: Analogies between options concepts and product family design

Stock Call Options	Real Options	Product Family Design
Current value of stock call option	(Gross) Present value of expected cash flow	Expected PFD value
Exercise price	Investment cost	Information content & value-added cycle time
Expiration time	Time until opportunity disappears	Time to market
Expected rate of return on the asset	Risk-free interest rate	Design flexibility & process flexibility
Volatility of asset (probability)	Project value uncertainty	Uncertainty of customer needs

Real options valuation generally consists of four major steps: (1) determine the natures of uncertainties involved, (2) identify real options, (3) value the options, and (4) make the optimal PFD decisions as shown in Figure 3-1.

Figure 3-1: Flow chart of the real options valuation

3.2 UNCERTAINTIES

To take into account the uncertainty involved in mass customization, PFD is modeled as a stochastic process. Under the options thinking, PFD involves two types of

uncertainties: exogenous and endogenous. Exogenous uncertainties are related to the market (e.g., price) and customer demand (Sanchez, 1991). Endogenous uncertainties refer to the probabilistic performance of each individual product variant derived from the PFD platform (Gonzalez-Zugasti, 2001).

3.2.1 Exogenous Uncertainty

Customer demand uncertainty has been the focus of project valuation (Kylaheiko *et al.*, 2002). Traditionally, it is interpreted based on a probabilistic distribution of the demand volume. While the volume criterion is more relevant to production capabilities (Bengtsson, 2001), satisfaction of customer needs is deemed to be the most important for product development projects (Gonzalez-Zugasti, 2001). In addition, the challenge of PFD results from proliferation of product variants, which entails uncertainties associated with diverse customer needs. Considering the inherent positive correlation between demand volumes and customer perceived utilities, this research models the customer demand uncertainty using the utility measure, i.e., $PU(CN_i)$.

A Geometric Brownian Motion (GBM) process is widely assumed to describe the stochastic behavior of a customer demand (Pindyck, 1988). In this context, the distribution of a customer perceived utility is characterized as a purely utility value driven Markov diffusion process or random walk that deviates according to GBM (Tannous, 1996). As a result, customer perceived utility, $PU(CN_i)$, deviates along a PFD project life and is described as a partial differential equation:

$$\frac{dPU(CN_i)}{dt} = PU(CN_i)_t - PU(CN_i)_{t-1}. \quad (3-1)$$

It further conforms to the properties of GBM (Pindyck, 1988): (1) It is a Markov process. All future values of the process depend only on its current value and are not affected by past values of the process or by any other current information. Therefore,

the current value of the process is all one needs to make a best forecast of its future value; (2) It has independent increments, whereby the change in the process over any time interval is independent of any other (non-overlapping) time interval; and (3) Changes in the process over any finite interval of time are log-normally distributed, with a variance that increases linearly with the time interval and always provides positive values. Since negative utility values of customer needs are meaningless, a log-normal distribution can be used. Hence, a stochastic $PU(CN_i)$ elapsing in GBM is formulated as the following:

$$dPU(CN_i) = \mu PU(CN_i)dt + \sigma PU(CN_i)dZ, \quad (3-2)$$

where μ and σ denote the expected rate of demand increase and demand volatility, respectively. Volatility of $PU(CN_i)$ drifts as a Wiener process at an increment, $dZ = e(t)\sqrt{dt}$, where $e(t) \sim N(0,1)$ is a serially uncorrelated and normally distributed random variable.

Suppose CN_i variegates within a range of functional specifications. Then $PU(CN_i)$ is further modeled in terms of utility values of its constituent functional features at a certain time, t , that is,

$$dPU_{F_{ij}}(CN_i) = \mu_{F_{ij}} PU(F_{ij}, t)dt + \sigma_{F_{ij}} PU(F_{ij}, t)dZ_{F_{ij}}, \text{ for all } F_{ij} \in \Lambda_{CN_i}^F, \quad (3-3)$$

where $\mu_{F_{ij}}$, $\sigma_{F_{ij}}$ and $dZ_{F_{ij}}$ are associated with each individual functional feature of CN_i . These coefficients are determined empirically based on specific characteristics of the market. For a given customer, $\Lambda_{CN_i}^F = \{F_{ij}\}_{j \in J_{CN_i}}$, the perceived utility is determined based on the additive multiple attribute utility theory (Butler *et al.*, 2001), as the following:

$$PU(CN_i) = \sum_{j=1}^{J_{CN_i}} w_j PU(F_{ij}), \quad (3-4)$$

where $\sum_{j=1}^{J_{CN_i}} w_j = 1$ denotes the relative importance among individual functional features, $\{F_{ij}\}_{J_{CN_i}}$; and $PU(F_{ij})$ falls within a binominal interval $[0,1]$ and stands for the part-worth utility of a specific functional feature, F_{ij} . Part-worth utilities are determined based on conjoint analysis (Green and Srinivasan, 1990).

3.2.2 Endogenous Uncertainty

Endogenous uncertainties of PFD are related to the technical performance of individual product variants. In accordance with the variant domain mapping process, two dimensions of uncertainties are identified, including customer satisfaction and process efficiency. These two measures exhibit the probabilistic behaviors of design performance in the design and process domains, respectively. Likewise, the GBM assumption is applicable to these endogenous uncertainties that can be regarded as a synchronous drift of customer need uncertainties, which causes ad hoc performance deviations of design modules and process variables.

(1) *Customer satisfaction.* Assume a design alternative, DA_k , consists of a set of design modules, $\{DM_m\}_{M_{DA_k}}$, that act as the DEs from a product platform in order to meet certain customer needs, $\{F_{mj}\}_{J_{DM_m}}$. For a particular functional requirement, F_{mj} , the customer expectation is described as a utility function, $PU(F_{mj})$, falling within the range $[F_{mj}^L, F_{mj}^U]$, where F_{mj}^L and F_{mj}^U are the lower and upper bounds of functional feature values, respectively. Over this range, customers usually demonstrate a varying degree of preference for different functional values.

From a technical viewpoint, the achieved customer satisfaction of a design module, DM_m , with respect to each functional feature, $\tilde{F}_{mj}$, generally conforms to a probabilistic distribution, $p(\tilde{F}_{mj})$, over the range $[\tilde{F}_{mj}^L, \tilde{F}_{mj}^U]$. Jiao and Tseng (2004) propose to measure customer satisfaction according to the probability of design success suggested by the overlap of distributions $p(\tilde{F}_{mj})$ and $PU(F_{mj})$, that is,

$$CS(DM_m) = \frac{1}{1 - \ln \int_{\tilde{F}_{mj}^L}^{\tilde{F}_{mj}^U} PU(F_{mj}) p(\tilde{F}_{mj}) dF_{mj}}. \quad (3-5)$$

The value of $CS(DM_m)$ ranges from 0 to 1, where $CS(DM_m) = 0$ indicates zero degree of customer satisfaction, and $CS(DM_m) = 1$ suggests the maximum degree of customer satisfaction. As a relative measure, $CS(DM_m)$ represents the relative performance of design module DM_m compared with the maximum amount possible.

The overall performance of design DA_k in terms of customer satisfaction depends on evaluations of multiple design modules, $\{DM_m\}_{M_{DA_k}}$, against multiple functional features, $\left\{ \left\{ F_{mj} \right\}_{J_{DM_m}} \right\}_{M_{DA_k}}$. This is achieved by further considering the correlations among many design modules, which is to be elaborated in the following Sections.

(2) *Process efficiency.* Each design alternative, DA_k , entails a set of process variables in the process domain, $\{PV_{mn}\}_{N_{DM_m}} \{M_{DA_k}\}$. These process variables perform as the DEs from a process platform in order to produce the design modules, $\{DM_m\}_{M_{DA_k}}$, contained in DA_k . The fulfillment of each process variable, PV_{mn} , requires certain production processes within the existing manufacturing capabilities. The performance of a process variable, PV_{mn} , in the process domain is thus measured in terms of its

expected process efficiency, $PE(PV_{mn})$, which implies the cost and manufacturability of DM_m in regard to PV_{mn} . The magnitude of process efficiency is determined based on the standard time estimation and variations of process capabilities (Jiao and Tseng, 2004). Considering the one-side specification limit, process efficiency is derived from the process capability index as the following,

$$PE(PV_{mn}) = \frac{USL_{PV_{mn}}^T - \mu_{PV_{mn}}^T}{3\sigma_{PV_{mn}}^T}, \quad (3-6)$$

where $USL_{PV_{mn}}^T$, $\mu_{PV_{mn}}^T$, and $\sigma_{PV_{mn}}^T$ are the upper specification limit, the average, and the standard deviation of the estimated cycle time of implementing PV_{mn} , respectively. Variations in the cycle time are characterized by $\mu_{PV_{mn}}^T$ and $\sigma_{PV_{mn}}^T$, reflecting the compound effect of PFD variants on production in terms of process variations. The $USL_{PV_{mn}}^T$ can be determined based on the worst case analysis of the corresponding process platform for DA_k , whereby generic routings are always used to accommodate various process variants, $\{PV_n\}_{N_{DA_k}}$. In practice, efforts in standard time study can also contribute to the evaluation of $USL_{PV_{mn}}^T$.

The process capability measure facilitates the evaluation of process variations in terms of cycle time performance. As there is a positive relationship between costs and the cycle time, this measure gives an indication of how expensive a design alternative is to be if implemented in accordance with the existing production processes. Moreover, modeling the cost property of PFD through cycle time and process variation performance can alleviate the difficulties in traditional cost estimation which turns to be tedious and less accurate.

3.3 REAL OPTIONS IDENTIFICATION

As far as a PFD project is concerned, the value of flexibility increases, as do options, when there is more risk. This is because the ability to avoid unfavorable circumstances or to take advantage of favorable opportunities is more valuable when there are greater prospects of exploiting flexibility inherent in product platforms. Investing into a PFD project creates options for the company to accommodate future customization requirements. The company possesses the flexibility to choose, over the course of developing product families, whether to develop variants based on existing platforms or develop the desired products individually, or to configure the desired products based on many options of platform elements. Flexibility of these real options bestows extra values to the company by hedging against volatility and turbulence in the market, design and production. Essentially, real options are properly identified which conform to the PFD configuration process.

PFD involves three aspects: common bases (CBs), differentiation enablers (DEs), and configuration mechanisms (CMs) (Du *et al.*, 2001). Customers' needs are characterized by combinations of functional features, each of which possesses a few values. A product family is designed to address the requirements of a group of customers in a market segment, in which customers share some common, along with certain distinct, functional feature values. From the design perspective, the product variants of the family are derived by configuring some CBs and certain DEs in terms of design parameters, which are preidentified for the product family. The CMs guarantee that only technologically-feasible and market-wanted product variants can be derived.

While the CBs exhibit the elements of a common product platform, DEs and CMs constitute the variety generation power of PFD. Correspondingly in the process domain, CBs comprise the process platform and DEs are characterized as process variables (Jiao

and Tseng, 2004). Within CMs, four variety generation methods are identified: attaching, removing, swapping, and scaling. More complicated product differentiation can be achieved through recursive application of these basic methods, namely variety nesting.

Corresponding to the PFD process, three types of real options are identified, including screening options dealing with platform-level decisions, configuring options handling product configuration, producing options coping with process configuration, and project-related options. All PFD real options are treated as European options, as any outcome of configuration would be meaningful until the expiration time, such that, stochastic changes can be made (Trigeorgis, 1996). For example, design flexibility of an earlier options execution represents the exercise value required to acquire a subsequent options to continue the operation of the project until the next installment of flexibility becomes due.

(1) Screening option. A screening option, $x^{SCRN}(\bullet)$, refers to the assessment of PFD platform spaces. Given a few product portfolios, $\{PpP_i\}_{I_{PpP}}$, the technical performance of each portfolio is determined based on the segment-level utility measure, $V(PpP_i) = PU(PpP_i)$. The screening decision regarding a portfolio is based on the financial valuation of its technical performance, i.e., $\tilde{V}(x^{SCRN}(PpP_i)) \leftarrow V(PpP_i)$. Only if the (financial) value of a screening option outperforms a pre-defined threshold, i.e., $\tilde{V}(x^{SCRN}(PpP_i)) \geq \tilde{V}(\Theta)$, this option can be exercised, meaning that portfolio PpP_i is selected to be used for a PFD platform.

Likewise, screening decisions regarding product and process platforms can be tackled according to the valuation of the respective screening option, i.e., $\{\tilde{V}(x^{SCRN}(PdP_i))\}_{I_{PdP}}$ and $\{\tilde{V}(x^{SCRN}(PcP_i))\}_{I_{PcP}}$, with respect to their technical

performances that are determined based on measuring customer satisfaction, $\{V(PdP_i) = CS(PpP_i)\}_{i \in PdP}$, and process efficiency, $\{V(PcP_i) = PE(PcP_i)\}_{i \in PcP}$, respectively,

(2) *Configuring options*. The configuring options, $x^{CONF}(\bullet)$ are related to the tasks of product configuration tasks from given design modules within a product platform. In accordance with the module manipulation mechanisms, configuring options include attaching option, $x^{ATTA}(DM_m)$, removing option, $x^{REMO}(DM_m)$, swapping option, $x^{SWAP}(DM_m, DM_q)$, and scaling option, $x^{SCAL}(DM_m)$. Corresponding to the nesting operation, a nesting real options is constructed from a series of basic configuring options, $x^{NEST}(\bullet)$. A nesting real options is only applicable to a subsystem that consists of multiple differentiation modules. For example, a nesting options may be giving as, $x^{NEST}(x^{ATTA}(DM_a)x^{REMO}(DM_b)x^{SCAL}(DM_c)x^{SWAP}(DM_d, DM_e))$. Illustrations of configuring options are provided in Table 3-2 where $m_{lj}(D_m)$ denotes modules at level l and D_m indicates a set of physical parts or a group of logic units performing particular functions j . Similarly, variant derivation decisions are made based on the configuring options valuation with respect to their technical performances measured in terms of expected customer satisfaction.

(3) *Producing option*. Process configuration decisions are modeled as producing options in regard to individual process variables, $\{x^{PROC}(PV_n)\}_N$. Among many process alternatives for fulfilling a design, DA_k , making choices among existing process variables, $\{\{PV_{mn}\}_{N_{DM_m}}\}_{M_{DA_k}}$, results in different process performances. A producing option is to be exercised only if this option excels in return of investment. Such financial performance is justified based on the valuation of the expected process efficiency, i.e., $\tilde{V}(x^{PROC}(PV_n)) \leftarrow V(PV_n) = PE(PV_n)$.

Table 3-2: Illustration of configuring options

Configuring Options	Descriptions
Attaching $x^{ATTA}(\bullet)$	<ul style="list-style-type: none"> ➤ Option allows those newly design modules which have unique functional features to fit exactly the customer need ➤ For example, the product variant x_1 is generated via attaching the module $m_{13}(\Delta D_3)$ at level 1, which performs a functional feature variant Δf_3 with its corresponding design parameters ΔD_3 on the product platform $PdP_1(F^*)$ of product family 1 ➤ Interfaces between modules must be compatible to each others
Removing $x^{REMO}(\bullet)$	<ul style="list-style-type: none"> ➤ In contrast to attaching option, option is exercised when there is an over-design in meeting customer preferences. Hence, those redundant modules have to be removed
Swapping $x^{SWAP}(\bullet)$	<ul style="list-style-type: none"> ➤ Option is undertaken when there is a difference in design parameters ΔD for the same functional requirement m_{12} and with the similar interfaces between both interchangeable modules ➤ It consists of the characteristics of both attaching and removing options
Scaling $x^{SCAL}(\bullet)$	<ul style="list-style-type: none"> ➤ Option is only employed if the changes of design parameter can be scale up or scale down, in rate k, where $k+1>1$ or $k+1<1$. Meanwhile, the module remains unchanged in the functional feature, i.e. fundamental technology, and the overall system structure
Nesting $x^{NEST}(\bullet)$	<ul style="list-style-type: none"> ➤ With this option, product variant can be generated through the $x^{SWAP}(\bullet)$ option between the modules m_{12}, which vary in the design parameters at scale g, and at the meantime, a $x^{SCAL}(\bullet)$ option is undertaken on the inherited modules m_{22} in rate k at the lower level.

(4) *Abandon option*. A straightforward rule for reaching a unique choice is the elimination of alternatives from a choice set (Ben-Akiva and Lerman, 1985). Hence, an abandon option, $x^{Aba}(\bullet)$, is introduced to discard whichever alternative that performs lower than a threshold level $\tilde{V}(\Theta)$. Nevertheless, the value of $x^{Aba}(\bullet)$ may rise if a salvage value is possible (Myers and Majd, 1983). This eventually leads to important managerial implications underlying one's choices on various production technologies and amount of investment when considering to abandon certain configuration alternatives.

3.4 VALUATION FRAMEWORK

Assuming that a firm targets a few market segments, i.e., $\{MS_s\}_S$, each market segment comprises a number of customers, i.e., $MS_s = \{CN_i\}_I$. Every customer is characterized by a set of customer needs that are specifications of some functional attributes, e.g., $CN_i = \{a_l, b_h, \dots, g_k\}$. A product family aims to meet the needs of some customers within the same segment. For example, given $CN_1 = \{a_1, a_2, a_3, b_2, b_8\}$, $CN_2 = \{a_1, b_1, b_2, b_3, c_1\}$, and $CN_3 = \{a_1, a_2, a_3, a_4, a_5, b_1, b_2, b_8\}$, it suggests that CN_1 possesses more commonality with CN_3 than with CN_2 . This means that customers CN_1 and CN_3 may belong to the same product family, whereas CN_2 is more relevant to another product family. Product family design generally involves two stages: platform determination and subsequently, variant derivation within a particular platform. While the selection of an appropriate platform involves the cohort performance of a group of customers, variant derivation concerns the individual performances of a few design alternatives with respect to a specific customer.

Platform determination is to decide the best platform for product family design to

start with. A PFD space comprises three dimensions, $\Lambda^{PFD} = \langle \Lambda^{PpP}, \Lambda^{PdP}, \Lambda^{PcP} \rangle$, where $\Lambda^{PpP} = \{PpP_i\}_{I^{PpP}}$, $\Lambda^{PdP} = \{PdP_i\}_{I^{PdP}}$ and $\Lambda^{PcP} = \{PcP_i\}_{I^{PcP}}$ refer to the product portfolio, product platform and process platform spaces, respectively. The screening of PFD platforms is based on the assessment of individual product portfolios, product platforms and process platforms at the market segment level. Product portfolios are evaluated based on the segment-level customer perceived utilities, $PU(\Lambda^{PpP}) = \{PU(PpP_i)\}_{I^{PpP}}$. The performance of each individual product platform is measured according to the achieved customer satisfaction with respect to a market segment, $CS(\Lambda^{PdP}) = \{CS(PdP_i)\}_{I^{PdP}}$. Process platforms are appraised in terms of their expected process efficiency, $PE(\Lambda^{PcP}) = \{PE(PcP_i)\}_{I^{PcP}}$. Based on the best values of these evaluations, an optimal PFD platform can be selected for a given CN_i , that is, $\hat{\Lambda}^{PFD} = \langle \hat{\Lambda}^{PpP}, \hat{\Lambda}^{PdP}, \hat{\Lambda}^{PcP} \rangle$, where $\hat{\Lambda}^{PpP} = \{PpP^*\}$, $\hat{\Lambda}^{PdP} = \{PdP^*\}$ and $\hat{\Lambda}^{PcP} = \{PcP^*\}$ are the best product portfolio (PpP^*), product platform (PdP^*) and process platform (PcP^*) for this CN_i , respectively.

Variant derivation involves the mapping from a specific CN_i to the variant spaces of a selected PFD platform, $\hat{\Lambda}^{PFD}$. It involves a consecutive mapping process between the functional, design and physical domains, which are characterized by sets of functional features, $\Lambda^F = \{F_j\}_J$, design modules, $\Lambda^{DM} = \{DM_m\}_M$ and process variables, $\Lambda^{PV} = \{PV_n\}_N$, respectively. To fulfill a given CN_i , variant derivation yields a few design alternatives, $\Lambda^{DA} = \{DA_k\}_K$. Each design alternative instantiates the functional, design and process domains with specific sets of functional features, $\hat{\Lambda}^F$, design modules, $\hat{\Lambda}^{DM}$ and process variables, $\hat{\Lambda}^{PV}$, respectively.

Ideally, the performance of a design alternative, $V(DA_k) = \langle PU(\hat{\Lambda}_{DA_k}^F), CS(\hat{\Lambda}_{DA_k}^{DM}), PE(\hat{\Lambda}_{DA_k}^{PV}) \rangle$, should correspond to the best value of each individual variant domain, $\langle PU^*(\Lambda^F), CS^*(\Lambda^{DM}), PE^*(\Lambda^{PV}) \rangle$. To avoid possible missing of some good solutions, the non-dominance rule is adopted in order to managing the many-to-many relationships inherent in the mappings between PFD variant domains. A threshold, $V(\Theta) = \langle PU(\Theta), CS(\Theta), PE(\Theta) \rangle$, is thus introduced to construct the solution space. As a result, PFD yields, rather than a single solution, a few good designs, $\hat{\Lambda}^{*DA} = \{DA_k^*\}_{K^*}$, that assume $V(\hat{\Lambda}^{*DA}) \geq V(\Theta)$, indicating that all these designs are “close to customer needs”. Figure 3-2 illustrates a PFD valuation framework. The general gist is to value all real options related to a PFD project for a customer chronologically along the project life span. PFD real options valuation assumes a competitive immunity environment, whereby direct competitive pressures from closely substitutable design alternatives are negligible. It also assumes that it is uneconomical for a firm to defeat a competitor with its proprietary technologies, superior market knowledge, exclusive distribution channels, and other superior capabilities.

3.4.1 Product Demand

In the PFD valuation framework, the product demand is modeled as customer perceived utilities. The demand process is stochastic and follows GBM, as given in Equation (3-3). Based on the real options theory, the mean value of product demand $PU_{F_j}(CN_i)$ at time t can be determined as the following,

$$E[PU(F_j, t)] = PU(F_j, 0)e^{\mu_i t}, \quad (3-7)$$

where $PU(F_j, 0)$ denotes the demand of product CN_i in terms of functional feature F_j at current time. Existing assets are assumed to span stochastic changes in demand

(Pindyck, 1988). This means that there exists an asset or a portfolio of assets whose price is perfectly correlated with $PU_{F_j}(CN_i)$. Thus, there should exist an asset or a dynamic portfolio of assets with price Ψ_{F_j} that is perfectly correlated with $PU_{F_j}(CN_i)$ and thereby also follows a GBM (Constantinides, 1978), that is,

$$d\Psi_{F_j} = \alpha_{F_j} \Psi_{F_j} dt + \sigma_{F_j} \Psi_{F_j} dz_{F_j}. \quad (3-8)$$

The expected rate of demand increase, μ_{F_j} , may differ from the drift rate, α_{F_j} , which is the equilibrium rate of return, although they have the same covariance as that of the market portfolio. Therefore, the drift rate of the asset, or the dynamic portfolio, has to be adjusted with regard to a factor, often called convenience yield, $\mu_{F_j} = \alpha_{F_j} - \delta_{F_j}$, in order to get the correct value of the options.

3.4.2 Payoff

The rationale that the options theory excels in real asset applications lies in that the payoff of the real options can be tailored to virtually any situation. Therefore, it is necessary to describe the payoff from real options according to decision rules, for which the simplest answer is a short mathematical expression. PFD decisions exhibit the same principle as that of financial options – design is accepted only if it meets certain customer needs. Similar to the way of dealing with financial options, the payoff from PFD options should be formulated mathematically according to their technical performances. Based on the options theory, the payoff from a long position in a European call option is given as the following,

$$\Psi_T = \max[S_T - X, 0], \quad (3-9)$$

where T is the expiration date, X is the strike price, and S_T is the final price of the underlying asset. The decision rule is that the options will be exercised if $S_T \geq X$ and not be exercised if $S_T < X$.

For a screening option, its payoff depends on its performance in terms of the customer perceived utility, given as the following,

$$\Psi(x^{SCRN}(CN_i)) = \max\left[\sum_{j=1}^{J_{CN_i}} w_j PU(F_j) - PU(\Theta), 0\right], \quad (3-10)$$

where $x^{SCRN}(CN_i)$ refers to a screening option, may it be a product portfolio, product platform or process platform, related to customer CN_i . Let $x^{CONF}(\bullet)$ denote a configuring option, may it be a $x^{ATTA}(\bullet)$, $x^{REMO}(\bullet)$, $x^{SCAL}(\bullet)$, $x^{SWAP}(\bullet)$, or $x^{NEST}(\bullet)$ option. The payoff of a configuring option is derived from its expected performance in terms of customer satisfaction, given as the following,

$$\Psi(x^{CONF}(DM_m)) = \max[CS(DM_m) - CS(\Theta), 0], \quad (3-11)$$

where DM_m is the design module, on which the configuring option operates. Likewise, the payoff of a producing option is determined as a type of European call options, given as the following,

$$\Psi(x^{PROC}(PV_n)) = \max[PE(PV_n) - PE(\Theta), 0], \quad (3-12)$$

where PV_n is the process variant associated with this producing option.

The payoff of an abandon option, however, depends on the savings from the if-otherwise exercised option. While an abandon option is enacted with design alternatives, its payoff is given as the following,

$$\Psi(x^{Aba}(DA_k)) = \sum_{m=1}^{M_{DA_k}} CS(DM_m^{DA_k}) + \sum_{n=1}^{N_{DA_k}} PE(PV_n^{DA_k}) - \sum_{j=1}^{J_{DA_k}} w_j PU(F_j^{DA_k}), \quad (3-13)$$

where $F_j^{DA_k}$, $DM_m^{DA_k}$, and $PV_n^{DA_k}$ are the respective functional features, design modules and process variables related to variant design DA_k .

Figure 3-2: Product family design valuation decision tree

3.5 PRICING MODEL

Two fundamental methods for pricing options are the binomial model and the Black-Scholes model (Trigeorgis, 1991). The values of PFD options manifest a paradigm of multivariate underlying assets represented by the demand of individual customers. Based on the options theory (Trigeorgis, 1996), the value of a PFD option must satisfy the following partial differential equation:

$$\frac{\partial \Psi(T)}{\partial t} + \sum_{i=1}^I (r - \delta_i) PU(CN_i) \frac{\partial \Psi(T)}{\partial PU(CN_i)} + \frac{1}{2} \sum_{i=1}^I \sum_{j=1}^I \rho_{ij} \sigma_i \sigma_j PU(CN_i) PU(CN_j) \frac{\partial^2 \Psi(T)}{\partial PU(CN_i) \partial PU(CN_j)} - r \Psi(T) = 0, \quad (3-14)$$

where r is a risk-free rate. Solving the above partial differential equation analytically is rather tedious and almost impossible. Thus, numerical solutions are always expected. A numerical options pricing technique is, therefore recommended for the valuation of such multivariate underlying assets in the subsequent chapter.

3.6 CASE STUDY

The proposed PFD real options framework is tested using an industrial case of vibration motors for mobile phones. Based on the analysis of historical data on the company's product fulfillment and existing manufacturing capabilities, the vibration motor product portfolios, product platforms and process platforms are constructed. The correspondence between functional features and design modules are summarized in Table 3-3. An illustration of a vibration motor in 3D exploded technical structure is given in Figure 3-3. Targeting the low- and high-end market segments, two respective vibration motor product platforms are established: PdP₁ and PdP₂. Two customer orders are selected for testing purpose: CNA and CNB, representing low- and high-end

customer needs, respectively. The specifications of individual customer needs and product platforms are given in Table 3-4.

Figure 3-3: 3D exploded technical structure of a vibration motor

Table 3-3: Functional features and the corresponding design modules

Functional Feature	Design Module
A1 – Current (mA)	Armature (A)
A2 – Pb free	
F1 – Length (mm)	Frame (F)
F2 – Diameter (mm)	
B1 – Color	Bracket (B)
B2 – Connected Method	
B3 – Coating	
W1 – Shape	Weight (W)
W2 – Holding Strength (kg)	
W3 – Speed (rpm)	
M1 – Pb free	Magnet (M)
RH1 – Color	Rubber Holder (RH)
RH2 – Shape	

Table 3-4: Specifications of customer needs and product platforms

Functional Feature	Individual Customer Needs		Product Platform	
	Customer CNA	Customer CNB	PdP ₁	PdP ₂
A1	60±15 / Triangular	80±20 / Triangular	[50, 70] / Triangular	[85, 110] / Triangular
A2	N / Uniform	Y / Uniform	[Y, N] / Uniform	[Y, N] / Uniform
F1	9.5±3 / Triangular	13.5±4 / Triangular	[8.5, 12] / Triangular	[14, 17] / Triangular
F2	10±4.5 / Triangular	19±8 / Triangular	[6.5, 15] / Triangular	[15, 27] / Triangular
B1	R / Uniform	B / Uniform	[R, W, B] / Uniform	[R, B, G] / Uniform
B2	U / Uniform	M / Uniform	[U, X, L] / Uniform	[U, M, T] / Uniform
B3	N / Uniform	Y / Uniform	[Y, N] / Uniform	[Y, N] / Uniform
W1	P / Uniform	U / Uniform	[P, T] / Uniform	[P, T, U] / Uniform
W2	4±2.5 / Triangular	5±3 / Triangular	[2.5, 5] / Triangular	[5.5, 8.5] / Triangular
W3	5500±200 / Triangular	10500±1500 / Triangular	[5000, 9200] / Triangular	[9500, 14000] / Triangular
M1	N / Uniform	Y / Uniform	[Y, N] / Uniform	[Y, N] / Uniform
RH1	R / Uniform	B / Uniform	[R, W, B] / Uniform	[R, B, G] / Uniform
RH2	P / Uniform	T / Uniform	[P, T] / Uniform	[P, T, U] / Uniform

3.6.1 Real Options Identification

Each product platform, for example PdP₁, supports a class of product family design. Figure 3-4 illustrates the established configuration mechanism within platform PdP₁, whereby product variants are generated by configuring options of variety generation on top of those common modules of the product architecture. Accordingly, PFD real options associated with PdP₁ and PdP₂ are identified, as shown in Table 3-5. Based on the identified real options, PDF for customer CNA based on PdP₁ is formulated, as shown in Figure 3-5.

Figure 3-4: Variety generation within platform PdP₁

3.6.2 Real Options Valuation

The valuation starts at the platform level, that is, the exercise of screening option. Given customer needs of CNA, all available screening options are valued. The result is shown in Figure 3-6. It is obvious that PdP₁ and PcP₁ yield an overall higher payoff

than that of PdP_2 and PcP_2 . Therefore, customer CNA should be fulfilled based on PdP_1 .

Within the selected platform PdP_1 for customer CNA, multiple configuring options are valuated at module-level. The goal is to achieve a higher overall value of the design.

Table 3-5: Real options associated with vibration motor family design

Screening Option, $x^{SCRN}(\bullet)$	$x^{SCRN}(PdP_1)$, $x^{SCRN}(PcP_1)$, $x^{SCRN}(PdP_2)$, $x^{SCRN}(PcP_2)$	
Configuring Options, $x^{CONF}(\bullet)$	Attaching Option, $x^{ATTA}(\bullet)$	$x^{ATTA}(A_{new})$, $x^{ATTA}(B_{new})$, $x^{ATTA}(W3_{new})$
	Removing Option, $x^{REMO}(\bullet)$	$x^{REMO}(A1)$, $x^{REMO}(B1)$, $x^{REMO}(W31)$
	Swapping Option, $x^{SWAP}(\bullet)$	$x^{SWAP}(F21, F23)$, $x^{SWAP}(B11, B13)$, $x^{SWAP}(B21, B22)$, $x^{SWAP}(B21, B23)$, $x^{SWAP}(W11, W12)$
	Nesting Option, $x^{NEST}(\bullet)$	$x^{NEST}(x^{SWAP}(B11, B13)x^{SWAP}(B21, B22))$, $x^{NEST}(x^{SWAP}(B11, B13)x^{SWAP}(B21, B23))$, $x^{NEST}(x^{SWAP}(W11, W12)x^{ATTA}(W3_{new})x^{REMO}(W31))$
Producing Option, $x^{PROC}(\bullet)$	$x^{PROC}(Fabrc\{Coil\})$, $x^{PROC}(Fabrc\{Bracket A\})$, $x^{PROC}(Fabrc\{Bracket B\})$, $x^{PROC}(Fabrc\{Terminal\})$, $x^{PROC}(Fabrc\{F\})$, $x^{PROC}(Assy\ Coil\{Tape, Commutator, Fabrc\{Coil\}\})$, $x^{PROC}(Assy\ A\{Shaft, Assy\ Coil\{Tape, Commutator, Fabrc\{Coil\}\}\})$, $x^{PROC}(Assy\ B\{Fabrc\{Bracket A, Bracket B, Terminal\}\})$, $x^{PROC}(Assy\ F\{Fabrc\ F, sub-part M\})$, $x^{PROC}(Assy\ Mainbody\{Assy\{A, F, B\}\})$, $x^{PROC}(Final\ Assy\{Assy\ Mainbody, sub-part RH, sub-part W\})$	
Abandon Option, $x^{Aba}(\bullet)$	$\{x^{Aba}(DA_1), x^{Aba}(DA_2), \dots, x^{Aba}(DA_k)\}$

Figure 3-5: Real options framework for customer CNA based on PdP_1

Figure 3-6: Payoff of screening options for customer CNA

The options participated are listed in Table 3-6. The payoff of each configuring options for customer CNA is shown in Figure 3-7. It is observed that three nesting options perform better than a threshold of 0.65. Therefore, the PFD for customer CNA should adopt these three configurations, while other configuration alternatives are discarded.

Table 3-6: Characteristics and valuation of producing options for customer CNA within

PcP₁

Producing Options	u^T	σ^T	USL^T	Payoff, $\psi(x^{PROC}(PV_n))$
$x^{PROC}(Fabrc\{Coil\})$	78.6	21.1	124.5	0.0651
$x^{PROC}(Fabrc\{Bracket A\})$	55.0	16.3	103.9	0.34
$x^{PROC}(Fabrc\{Bracket B\})$	33.7	10.6	61.2	0.2048
$x^{PROC}(Fabrc\{Terminal\})$	14.6	7.8	21.2	0.01
$x^{PROC}(Fabrc\{F\})$	29.4	10.7	60.3	0.3026
$x^{PROC}(Assy\ Coil\{Tape, Commutator, Fabrc\{Coil\}\})$	22.3	8.5	37.6	0.03
$x^{PROC}(Assy\ A\{Shaft, Assy\ Coil\{Tape, Commutator, Fabrc\{Coil\}\}\})$	18.8	7.7	40.0	0.2577
$x^{PROC}(Assy\ B\{Fabrc\{Bracket A, Bracket B, Terminal\}\})$	15.5	6.3	22.3	0.025
$x^{PROC}(Assy\ F\{Fabrc\ F, sub-part\ M\})$	35.5	8.2	55.0	0.1327
$x^{PROC}(Assy\ Mainbody\{Assy\{A, F, B\}\})$	30.5	6.2	45.0	0.1196
$x^{PROC}(Final\ Assy\{Assy\ Mainbody, sub-part\ RH, sub-part\ W\})$	20.8	9.4	47.5	0.2868

At the production stage, CNA design alternatives are evaluated according to the payoffs of available producing options. The characteristics of producing options for customer CNA within PcP₁ are summarized in Table 3-6. All these producing options

are valued, as shown in Figure 3-8. It suggests a threshold of 0.066, based on which feasible producing options are exercised for the production of CNA design.

Figure 3-7: Payoff of configuring options for customer CNA within PdP₁

Figure 3-8 indicates that certain producing options are not beneficial. This may be due to limitation of existing manufacturing capacities. In practice, companies deal with these low value-added processes through subcontracting them or outsourcing the required component parts or modules to suppliers. Overall, the PFD for customer CNA yields a value of 4.0207 by configuring from real options. Therefore, the abandon option is infeasible to employ in this case.

Figure 3-8: Payoff of producing options for customer CNA within PcP₁

Most importantly, real options approach leads to significant improvements in the value of PFD by recognizing the value of flexibility either inherent in a project or that can be built in product platforms. These improvements are more promising when uncertain demands are concerned, and when the downstream costs are relatively large.

3.7 SUMMARY

This chapter presents real options identification and valuation as a practical and effective framework to evaluate product family design. The financial analysis clarifies the value of management control and the exercise of choices at key decision points along the PFD project life. It permits a consistent choice of the risk-free discount rate for the valuation, because the project risks can be diversified and the market risks are accounted for by the options analysis. The identification and valuation of real options shed light on the analysis of value-cost tradeoffs underlying product platforms and family design. Real options models thus deserve a place in toolkits of decision making due to high uncertainty and costs of irreversible investment in PFD.

CHAPTER 4:

A NUMERICAL OPTIONS PRICING APPROACH TO PRODUCT FAMILY DESIGN VALUATION

This chapter extends the contingent claims valuation (Black and Scholes, 1973; Merton, 1973) approach to the case of product family design valuation under uncertainty. The classic Black-Scholes formula is adopted to determine the price of a call option in a closed form under a dynamic geometric Brownian motion (Dixit and Pindyck, 1994). PFD involves many options that incorporate with multivariate payoffs. While the formulation of the options pricing model is straightforward, the computation of payoffs is tedious and thus is very difficult, if not impossible, to obtain any analytical solution. In this regard, several financial practitioners have resorted to numerical approaches, such as numerical integration, Monte Carlo simulations, lattice, and approximations approaches. When dealing with the high dimensions, numerical approaches may suffer from low computational efficiency for practical purposes. This chapter emphasizes on practical numerical approaches for PFD options pricing, owing to their intuitive simplicity, flexibility and easiness in handling all kinds of complex options.

4.1 NUMERICAL OPTIONS PRICING APPROACHES

In general, there are two types of numerical options pricing approaches: direct (implicit or explicit numerical discretization) and indirect (Monte-Carlo simulation or lattice-based approaches) approaches, as shown in Table 4-1. Numerical methods enhance the ability of risk neutral valuation involving tedious computation. Studies

suggest that the simulation approach is simple and flexible, but lacks accuracy whereby consists standard errors and low computational efficiency (Bengtsson *et al.* 2002). Moreover, it is only applicable to European-type options valuation. Finite-difference approaches can be used to value American as well as European options, and are more efficient provided a whole set of starting options value is known. However, it may not be readily used with history dependent payoffs, and cannot be used at all when the partial differential equations describing the options value dynamics are not specified. Therefore, it is more mechanical and less intuition than lattice approaches.

Table 4-1: Numerical options pricing approaches (Schwartz *et al.*, 2001)

Stochastic Processes (SP)	Partial Differential Equations (PDE) / Black-Scholes Approach
Monte Carlo Simulation (MCS)	Numerical Integration (NI)
Lattice Approach(LA) ➤ Std. Binomial Lattice Approach (SBLM) ➤ Log-Transformed Binomial Approach (LTBM)	Implicit Finite Difference Schemes (IFDS) / Explicit Finite Difference Schemes (EFDS)
	Analytic Approximations (AA) ➤ Compound-Option Analytic Polynomial Approximation (COAPA) ➤ Quadratic Approximation (QA) ➤ Various Problem-Specific Heuristic Approximation (VPSHA)

Lattice approaches are generally more intuitive, simpler, and more flexible in handling different stochastic processes, options payoffs, early exercise or other intermediate decisions, several underlying variables, and so on. Meanwhile, the main limitations of lattice approaches, such as Cox, Ross, and Rubiustein (CRR), Boyle, Evnine, and Gibbs (BEG), and NEK approaches, are their inability to handle more than one starting price at a time. In addition, Trigeorgis (1991) observe the inconsistency, instability, and inefficiency of the CRR approach which is the lattice binomial approach by Cox, Ross, and Rubiustein (1979) in valuing American options for one asset cases. Consistency, defined as the discrete-time process used for computation has the same

mean and variance for every time-step size as that of the underlying continuous process. Further, stability means that the approximation errors in the computation process are dampened out rather than amplified. Efficiency refers to the number of operations or amount of operations or computing time needed for achieving the accuracy of a given approximation (Trigeorgis, 1991).

Similarly, the extended CRR approach which is referred as the BEG approach is proposed by Boyle, Evnine, and Gibbs (1989), which takes the case of several assets into consideration. However, the problems such as poor consistency, stability and efficiency still exist in BEG approach. Ekvall (1996) develops a lattice approach namely NEK approach to overcome those problems encountered by the BEG approach. Unfortunately, NEK approach is unable to guarantee the consistency of jump probability while the fixed probabilities are undertaken and jump sizes are determined later. A log-transformed binomial lattice (LTBL) approach for valuing options with one underlying asset is designed, which overcomes known problems of above mentioned approaches by Trigeorgis (1996). Furthermore, a three-dimensional lattice approach (Hull and White, 1993) and a Multidimensional LTBL (MLTBL) approach (Gamba and Trigeorgis, 2004) are reported to work well with interrelated multidimensional options while achieving the numerically attractive features obtained in LTBL.

4.2 MLTBL APPROACH TO VALUATION

MLTBL approach is an extended approach of Trigeorgis's LTBL approach for valuating one asset to the case of several assets. In implementing such approach, it is necessary to transform the risk-neutral process described by Equation (4-1) into a system of uncorrelated processes (Ekvall, 1996).

$$\frac{dPU(CN_i)}{PU(CN_i)} = \mu dt + \sigma dZ, \quad (4-1)$$

4.2.1 Transformation

Assuming a risk-neutral process is adopted to GBM as shown in above Equation (4-1), the process can subsequently be transformed to an Itô process with constant instantaneous drifts and standard deviations by the following simple logarithmic transformation:

$$dv_i = d(\ln V_i) = (r - \frac{1}{2}\sigma_i^2)dt + \sigma_i dZ_i \quad i = 1, 2, \dots, n \quad (4-2)$$

Introduce the vector:

$$d\mathbf{v} = [dv_1, dv_2, \dots, dv_n]^T, \quad (4-3)$$

where T denotes the transpose. Since $Z_i, i = 1, 2, \dots, n$, are Wiener processes, Equations (4-2) and (4-3) are deduced as Equation (4-4).

$$d\mathbf{v} \sim N_n([\mathbf{r} - \frac{1}{2}\boldsymbol{\sigma}^2]dt, \boldsymbol{\Omega}dt), \quad (4-4)$$

where $N_n(\cdot; \cdot)$ denotes the n-variate normal distribution,

$[\mathbf{r} - \frac{1}{2}\boldsymbol{\sigma}^2] = [(r - \frac{1}{2}\sigma_1^2), (r - \frac{1}{2}\sigma_2^2), \dots, (r - \frac{1}{2}\sigma_n^2)]^T$, and

$$\boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_{12} & \cdots & \sigma_1\sigma_n\rho_{1n} \\ \sigma_1\sigma_2\rho_{12} & \sigma_2^2 & \cdots & \sigma_2\sigma_n\rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_1\sigma_n\rho_{1n} & \sigma_2\sigma_n\rho_{2n} & \cdots & \sigma_n^2 \end{bmatrix}.$$

Assuming that all of the underlying assets are distinct (see Ekvall (1996)), therefore, $\boldsymbol{\Omega}$ will be a symmetric and positive definite matrix, and hence can be Cholesky factorized. Thus, $\boldsymbol{\Omega}$ can be rewritten as:

$$\boldsymbol{\Omega} = \mathbf{A}\mathbf{A}^T, \quad (4-5)$$

where $\mathbf{A}$ is a lower triangular matrix, which can be inverted easily.

Since a linear combination of normally distributed variables is normally distributed, the vector is introduced as Equation (4-6).

$$dw = (w_1, w_2, \dots, w_n) \equiv \mathbf{A}^{-1} d\mathbf{v}, \quad (4-6)$$

which is distributed as:

$$dw \sim N_n(\mathbf{L}dt, \mathbf{I}dt), \quad (4-7)$$

where $\mathbf{L} = (L_1, L_2, \dots, L_n)^T = \mathbf{A}^{-1}[\mathbf{r} - \frac{1}{2}\boldsymbol{\sigma}^2]$ and $\mathbf{I}$ is the $(n \times n)$ -dimensional identity matrix. Thus, Equation (4-7) gives the desired system of an uncorrelated process.

4.2.2 Jump Sizes and Jump Probabilities

The results can be presented based on the assets underlying PFD. Cases to be demonstrated in this section are one-asset, two assets, and n -asset cases. Firstly, let H_i be the up-jump size of the transformed state variable w_i , the down-jump size of the transformed state variable be $-H_i$ and $P_{i_1, i_2, \dots, i_n}$ be the jump probability, where

$$i_j = \begin{cases} 1 & \text{if state variable } j \text{ jumps upwards} \\ 0 & \text{otherwise} \end{cases} \quad j = 1, 2, \dots, n$$

(1) *One-asset case.* The LTBL approach designed by Trigeorgis (1991) defines the jump size and the jump probabilities as follows:

$$H_1 = \sqrt{\Delta t + L_1^2 \Delta t^2}, \quad (4-8a)$$

$$P_1 = \frac{1}{2} \left(1 + \frac{L_1 \Delta t}{H_1} \right), \quad (4-8b)$$

$$P_0 = 1 - P_1 = \frac{1}{2} \left(1 - \frac{L_1 \Delta t}{H_1} \right), \quad (4-8c)$$

(2) *Two assets case.* Consider any differential time interval, Δt , Equation (3-8) follows directly that:

$$w = (w_1, w_2) \sim N_2(\mathbf{L}\Delta t, \mathbf{I}\Delta t), \quad (4-9)$$

which has the characteristic function (see Liu (2000)) as in Equation (4-10).

$$\Psi_c(\theta_1, \theta_2) = E[\exp(i\theta_1 w_1 + i\theta_2 w_2)] = \exp\left[i\Delta t(\theta_1 L_1 + \theta_2 L_2) - \frac{\Delta t}{2}(\theta_1^2 + \theta_2^2)\right], \quad (4-10)$$

where i is the imaginary unit ($i = \sqrt{-1}$) and θ_i is a real number ($i = 1, 2$). Expanding the right-hand side as a Taylor series, leads to Equation (4-11).

$$\begin{aligned} & \Psi_c(\theta_1, \theta_2) \\ &= 1 + i\Delta t(\theta_1 L_1 + \theta_2 L_2) - \frac{\Delta t}{2}(\theta_1^2 + \theta_2^2) - \frac{\Delta t^2}{2}(\theta_1 L_1 + \theta_2 L_2)^2 + o(\Delta t) \\ &= 1 + i\theta_1 \cdot L_1 \Delta t + i\theta_2 \cdot L_2 \Delta t - \frac{\theta_1^2}{2}(\Delta t + L_1^2 \Delta t^2) - \frac{\theta_2^2}{2}(\Delta t + L_2^2 \Delta t^2) - \theta_1 \theta_2 \cdot L_1 L_2 \Delta t^2 + o(\Delta t) \end{aligned} \quad , \quad (4-11)$$

For the discrete four-jump distribution, the characteristic function can be written as Equation (4-12).

$$\Psi_d(\theta_1, \theta_2) = P_{11}e^{i\theta_1 H_1 + i\theta_2 H_2} + P_{10}e^{i\theta_1 H_1 - i\theta_2 H_2} + P_{01}e^{-i\theta_1 H_1 + i\theta_2 H_2} + P_{00}e^{-i\theta_1 H_1 - i\theta_2 H_2}, \quad (4-12)$$

Expanding the right-hand side as a Taylor series, results into Equation (4-13).

$$\begin{aligned} & \Psi_d(\theta_1, \theta_2) \\ &= P_{00}\left[1 + (-i\theta_1 H_1 - i\theta_2 H_2) + \frac{1}{2}(-i\theta_1 H_1 - i\theta_2 H_2)^2\right] \\ &+ P_{10}\left[1 + (i\theta_1 H_1 - i\theta_2 H_2) + \frac{1}{2}(i\theta_1 H_1 - i\theta_2 H_2)^2\right] \\ &+ P_{01}\left[1 + (-i\theta_1 H_1 + i\theta_2 H_2) + \frac{1}{2}(-i\theta_1 H_1 + i\theta_2 H_2)^2\right] \\ &+ P_{11}\left[1 + (i\theta_1 H_1 + i\theta_2 H_2) + \frac{1}{2}(i\theta_1 H_1 + i\theta_2 H_2)^2\right] + o(\Delta t) \\ &= (P_{11} + P_{10} + P_{01} + P_{00}) + i\theta_1 \cdot H_1(P_{11} + P_{10} - P_{01} - P_{00}) + i\theta_2 \cdot H_2(P_{11} - P_{10} + P_{01} - P_{00}) \\ &- \frac{\theta_1^2}{2} \cdot H_1^2 - \frac{\theta_2^2}{2} \cdot H_2^2 - i\theta_1 \theta_2 \cdot H_1 H_2(P_{11} - P_{10} - P_{01} + P_{00}) + o(\Delta t) \end{aligned} \quad , \quad (4-13)$$

Ensuring convergence between the discrete distribution and its continuous bivariate normal counterpart, the coefficients in Equations (4-11) and (4-13) are equated. Following Equations (4-14a) ~ (4-14f) are derived.

$$H_1^2 = \Delta t + L_1^2 \Delta t^2, \quad (4-14a)$$

$$H_2^2 = \Delta t + L_2^2 \Delta t^2, \quad (4-14b)$$

$$P_{11} + P_{10} + P_{01} + P_{00} = \sum_{i,j=0}^1 P_{ij} = 1, \quad (4-14c)$$

$$P_{11} + P_{10} - P_{01} - P_{00} = \sum_{i,j=0}^1 (-1)^{i+1} P_{ij} = \frac{L_1 \Delta t}{H_1}, \quad (4-14d)$$

$$P_{11} - P_{10} + P_{01} - P_{00} = \sum_{i,j=0}^1 (-1)^{j+1} P_{ij} = \frac{L_2 \Delta t}{H_2}, \quad (4-14e)$$

$$P_{11} - P_{10} - P_{01} + P_{00} = \sum_{i,j=0}^1 (-1)^{i+j} P_{ij} = \frac{L_1 L_2 \Delta t^2}{H_1 H_2}, \quad (4-14f)$$

By solving the above system, following Equations are deduced.

$$H_1 = \sqrt{\Delta t + L_1^2 \Delta t^2}, \quad (4-15a)$$

$$H_2 = \sqrt{\Delta t + L_2^2 \Delta t^2}, \quad (4-15b)$$

$$P_{11} = \frac{1}{4} \left(1 + \frac{L_1 \Delta t}{H_1} \right) \cdot \left(1 + \frac{L_2 \Delta t}{H_2} \right), \quad (4-15c)$$

$$P_{10} = \frac{1}{4} \left(1 + \frac{L_1 \Delta t}{H_1} \right) \cdot \left(1 - \frac{L_2 \Delta t}{H_2} \right), \quad (4-15d)$$

$$P_{01} = \frac{1}{4} \left(1 - \frac{L_1 \Delta t}{H_1} \right) \cdot \left(1 + \frac{L_2 \Delta t}{H_2} \right), \quad (4-15e)$$

$$P_{00} = \frac{1}{4} \left(1 - \frac{L_1 \Delta t}{H_1} \right) \cdot \left(1 - \frac{L_2 \Delta t}{H_2} \right), \quad (4-15f)$$

(3) *n-asset case*. The development of n assets parallels that of the two-asset case. As above, the characteristic functions of the discrete distribution and its continuous counterpart are assigned to ensure convergence of the two distributions. Following some algebraic operations, a set of linear equations for the jump sizes H_k and the jump probabilities $P_{i_1, i_2, \dots, i_n}$ are generated. Corresponding to Equations (4-8a), (4-14a) and (4-14b), a set of n equations is obtained as Equation (4-16a)

$$H_k^2 = \Delta t + L_k^2 \Delta t^2 \quad 1 \leq k \leq n, \quad (4-16a)$$

and the jump sizes can be written as $H_k = \sqrt{\Delta t + L_k^2 \Delta t^2}$. Corresponding to Equation (4-14c), Equation (4-16b) is yielded.

$$\sum_{i_1, i_2, \dots, i_n=0}^1 P_{i_1, i_2, \dots, i_n} = 1, \quad (4-16b)$$

which explains that there will be 2^n possible values for the n assets after any differential time interval, Δt . Corresponding to Equations (4-14d) and (4-14e), n equations are derived as follows:

$$\sum_{i_1, i_2, \dots, i_n=0}^1 (-1)^{i_k+1} P_{i_1, i_2, \dots, i_n} = \frac{L_k \Delta t}{H_k} \quad 1 \leq k \leq n, \quad (4-16c)$$

Corresponding to Equation (4-14f), a set of $\frac{n(n-1)}{2}$ equations is generated as follows:

$$\sum_{i_1, i_2, \dots, i_n=0}^1 (-1)^{i_k+i_m} P_{i_1, i_2, \dots, i_n} = \frac{L_k L_m \Delta t^2}{H_k H_m} \quad 1 \leq k < m \leq n, \quad (4-16d)$$

Equations (4-16b), (4-16c) and (4-16d) constitute a set of $\frac{n^2 + 3n + 2}{2}$ equations for 2^n unknown jump probabilities $P_{j_1, j_2, \dots, j_n}$. For $n=1$ and $n=2$, the number of equations is exactly equal to the number of unknowns. For $n \geq 3$, the number of unknowns exceeds the number of equations so that there are theoretically an infinite number of solutions. However, an exact solution can be formulated from the symmetry of the expressions which are the Equations (4-8b), (4-8c), (4-15c), (4-15d), (4-15e), and (4-15f) that derived in the one-asset and two-asset cases. The solution is given as follows:

$$P_{i_1, i_2, \dots, i_n} = \frac{1}{2^n} \prod_{k=1}^n \left[1 + (-1)^{i_k} \frac{L_k \Delta t}{H_k} \right], \quad (4-17)$$

It can be verified by direct substitution that the probabilities given by Equation (4-17) do indeed satisfy Equations (4-16b), (4-16c) and (4-16d).

4.3 MLTBL IMPLEMENTATION

In general, analytic solutions for the multi-dimensional PFD valuation do not exist; thus, ultimately the MLTBL approach is integrated to compute the options value, $\Psi(T)$, numerically at time to market T , which is denoted as the following,

$$\frac{\partial \Psi(T)}{\partial t} + \sum_{i=1}^I (r - \delta_i) PU(CN_i) \frac{\partial \Psi(T)}{\partial PU(CN_i)} + \frac{1}{2} \sum_{i=1}^I \sum_{j=1}^I \rho_{ij} \sigma_i \sigma_j PU(CN_i) PU(CN_j) \frac{\partial^2 \Psi(T)}{\partial PU(CN_i) \partial PU(CN_j)} - r \Psi(T) = 0$$

The implementation of binomial lattice approach is straightforward where the key idea is to choose jump sizes and jump probabilities (Ekvall, 1996). As the underlying individual customers' demands (state variables) are correlated, it is necessary to transform them to uncorrelated variables. First, taking the logarithm of the underlying state variables, that is, $v_i = \ln PU(CN_{i=1,2,\dots,n})$. More specifically, Ito's Lemma implies that the stochastic differentials $v_{i=1,2,\dots,n}$, assume as the following,

$$dv_i = \left(r - \frac{1}{2} \sigma_i^2 \right) dt + \sigma_i dZ_i, \quad i = 1, 2, \dots, n \quad (4-18)$$

Introduce a vector: $dv_i = [dv_1, dv_2, \dots, dv_n]^T$, where T denotes the transpose. Since $Z_{i=1,2,\dots,n}$ conform to the Wiener process, Equation (4-18) yields as follows,

$$dv \sim N_n \left(\left[r - \frac{1}{2} \sigma^2 \right] dt, \Omega dt \right), \quad (4-19)$$

where $N_n(\cdot, \cdot)$ denotes the n-variate normal distribution

$$\left[r - \frac{1}{2} \sigma^2 \right] = \left[\left(r - \frac{1}{2} \sigma_1^2 \right), \left(r - \frac{1}{2} \sigma_2^2 \right), \dots, \left(r - \frac{1}{2} \sigma_n^2 \right) \right]^T, \text{ and}$$

$$\Omega = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_{12} & \cdots & \sigma_1\sigma_n\rho_{1n} \\ \sigma_1\sigma_2\rho_{12} & \sigma_2^2 & \cdots & \sigma_2\sigma_n\rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_1\sigma_n\rho_{1n} & \sigma_2\sigma_n\rho_{2n} & \cdots & \sigma_n^2 \end{bmatrix}$$

Assuming all of the underlying assets is distinct. Then Ω will be a symmetric and positive definite matrix, and hence can be Cholesky factorized. Thus, Ω can be rewritten as $\Omega = AA^T$, where A is a lower triangular matrix, which can be inverted easily. Since a linear combination of normally distributed variables is normally distributed, a vector $dw \equiv A^{-1}dv$ is introduced. It is distributed as:

$$dw \sim N_n(Ldt, Idt), \quad (4-20)$$

where $L = [L_1, L_2, \dots, L_n]^T = A^{-1} \left[r - \frac{1}{2} \sigma^2 \right]$, and I is the $(n \times n)$ -dimensional identity matrix. It is, of course, assumed that $w(t_0) = A^{-1}v(t_0)$. Therefore, n -transformed state variables are uncorrelated. The up-jump size u_k (the down-jump size $d_k = 1/u_k$) and the up-jump probability p_k of the k -th variable w_k are determined as follow,

$$u_k = e^{\sqrt{\Delta t + L_k^2 \Delta t^2}}, \quad (4-21)$$

$$P_{i_1, i_2, \dots, i_n} = \frac{1}{2^n} \prod_{k=1}^n \left[1 + (-1)^{i_k} \frac{L_k \Delta t}{H_k} \right], \quad (4-22)$$

where $\Delta t = T/N$ is the length of a time step, N is the number of time steps that T is divided into.

Following the transformations based on one-to-one mappings, there exists an invertible function from the original state variables to the transformed state variables. To be more exact, the invertible function is,

$$[PU(CN_1), PU(CN_2), \dots, PU(CN_n)]^T = [e^{v_1}, e^{v_2}, \dots, e^{v_n}]^T, \quad (4-23)$$

where $[v_1, v_2, \dots, v_n]^T = A[w_1, w_2, \dots, w_n]^T$.

From Equations (4-21) thru (4-23), the demand and the probability of each node in the n -variate binomial tree can be obtained. Then the payoffs from the real options on each node can be calculated based on Equations (3-10) through (3-13), in which the payoffs from real options may be different under different situations. Thus, the values of real options at current time are given as:

$$V = e^{-rT} \sum_{j_1, j_2, \dots, j_n=0}^N \left\{ \prod_{i=1}^n \frac{N!}{j_i! (N-j_i)!} p_k^{j_i} (1-p_k)^{N-j_i} \right\} V_{j_1, j_2, \dots, j_n}, \quad (4-24)$$

where $V_{j_1, j_2, \dots, j_n}$ indicates the payoff from real options on the time-to-market T when the transformed state variable, $w_{k=1,2,\dots,n}$ has jumped upwards j_k times. The number of down-jumps is given by N minus the number of up-jumps.

4.4 MLTBL ANALYSIS

This section compares the MLTBL approach with other known lattice approaches including BEG and NEK approaches, such typical aspects as consistency, stability, and efficiency are investigated.

4.4.1 Consistency

For a continuous process, the increment w is normally distributed as $N_n(\mathbf{L}\Delta t, \mathbf{I}\Delta t)$.

For a discrete-time process, the means are formulated as the following:

$$E(w_k) = \sum_{i_1, i_2, \dots, i_n=0}^1 (-1)^{i_k+1} P_{i_1, i_2, \dots, i_n} H_k = H_k \sum_{i_1, i_2, \dots, i_n=0}^1 (-1)^{i_k+1} P_{i_1, i_2, \dots, i_n} \quad 1 \leq k \leq n, \quad (4-25)$$

By substituting Equation (4-16c), Equation (4-25) can be rewritten as Equation (4-26).

$$E(w_k) = H_k \cdot \frac{L_k \Delta t}{H_k} = L_k \Delta t \quad 1 \leq k \leq n, \quad (4-26)$$

where the variances are derived in Equation (4-27).

$$\begin{aligned}
Var(w_k) &= \sum_{i_1, i_2, \dots, i_n=0}^1 P_{i_1, i_2, \dots, i_n} [(-1)^{i_k+1} H_k - E(w_k)]^2 \\
&= [H_k^2 + E(w_k)^2] \sum_{i_1, i_2, \dots, i_n=0}^1 P_{i_1, i_2, \dots, i_n} - 2H_k E(w_k) \sum_{i_1, i_2, \dots, i_n=0}^1 (-1)^{i_k+1} P_{i_1, i_2, \dots, i_n}
\end{aligned} \tag{4-27}$$

Substituting Equations (4-16a), (4-16b) and (4-16c) into Equation (4-27), Equation (4-28) is deduced.

$$Var(w_k) = \Delta t = \left[\Delta t + L_k^2 \Delta t^2 \right] + L_k^2 \Delta t^2 - 2H_k \cdot L_k \Delta t \cdot \frac{L_k \Delta t}{H_k} \tag{4-28}$$

The covariances are expressed as Equation (4-29).

$$\begin{aligned}
Cov(w_k, w_m) &= \sum_{i_1, i_2, \dots, i_n=0}^l P_{i_1, i_2, \dots, i_n} [(-1)^{i_k+1} H_k - E(w_k)] [(-1)^{i_m+1} H_m - E(w_m)] \\
&= H_k H_m \sum_{i_1, i_2, \dots, i_n=0}^l (-1)^{i_k+i_m} P_{i_1, i_2, \dots, i_n} - E(w_k) H_m \sum_{i_1, i_2, \dots, i_n=0}^l (-1)^{i_m+1} P_{i_1, i_2, \dots, i_n} \\
&\quad - H_k E(w_m) \sum_{i_1, i_2, \dots, i_n=0}^l (-1)^{i_k+1} P_{i_1, i_2, \dots, i_n} + E(w_k) E(w_m) \sum_{i_1, i_2, \dots, i_n=0}^l P_{i_1, i_2, \dots, i_n}
\end{aligned} \tag{4-29}$$

Substituting Equations (4-16b), (4-16c) and (4-16d) into Equation (4-29), Equation (4-30) is deduced.

$$\begin{aligned}
Cov(w_k, w_m) &= H_k H_m \frac{v_k v_m \Delta t^2}{H_k H_m} - v_k \Delta t H_m \frac{v_m \Delta t}{H_m} - H_k v_m \Delta t \frac{v_k \Delta t}{H_k} + v_m \Delta t v_k \Delta t \\
&= v_k v_m \Delta t^2 - v_k v_m \Delta t^2 - v_k v_m \Delta t^2 + v_k v_m \Delta t^2 \\
&= 0
\end{aligned} \tag{4-30}$$

As the discrete-time process has the same means and variances for every time-step size as that of the underlying continuous process, thus consistency is proved (Trigeorgis, 1991).

4.4.2 Stability

From Equations (4-16a), subsequent inequalities are derived.

$$-H_k < \pm L_k \Delta t < H_k = \sqrt{\Delta t + L_k^2 \Delta t^2} \tag{4-31}$$

Therefore,

$$0 = \frac{1}{2} \left(1 - \frac{H_k}{H_k}\right) < \frac{1}{2} \left(1 \pm \frac{L_k \Delta t}{H_k}\right) < \frac{1}{2} \left(1 + \frac{H_k}{H_k}\right) = 1 \quad k = 1, 2, \dots, n \quad (4-32)$$

and

$$0 < \frac{1}{2^n} \prod_{k=1}^n \left[1 + (-1)^{i_k} \frac{L_k \Delta t}{H_k}\right] = \prod_{k=1}^n \frac{1}{2} \left[1 + (-1)^{i_k} \frac{L_k \Delta t}{H_k}\right] < 1 \quad (4-33)$$

From Equations (4-17), Equation (4-34) is obtained.

$$0 < P_{i_1, i_2, \dots, i_n} < 1 \quad i_1, i_2, \dots, i_n = 0, 1 \quad (4-34)$$

As the summation of the jump probabilities is equal to 1 and is constrained between 0 and 1, the valuation procedure is unconditionally stable (Trigeorgis, 1991).

4.4.3 Efficiency

The efficiency analysis compares the accuracy of the MLTBL approach with the accuracies of the BEG and NEK approaches. The efficiency of a numerical approach is usually influenced by the values of the parameters. Same sets of parameter values as used by Ekvall (1996) are adopted in order to show the efficiency of the MLTBL approach.

Assume that the riskless rate $r = 0.10$, the time to maturity $T = 1.0$, the exercise price $K = 10.0$, and the current prices of the underlying assets $V_i(0) = 10.0$ ($i = 1, 2, \dots, n$). The correlation coefficients between the underlying assets ρ_{ij} and the standard deviations of the underlying assets σ_i vary. The results obtained are shown in Table 4-2, where the MLTBL approach is proven more efficient over the BEG approach in most cases, while avoiding the possibility of negative jump probabilities. Comparing with the NEK approach, the MLTBL approach demonstrates similar performances. In addition, the MLTBL approach achieves a maximum error less than 1.7% with 10 time steps. Nevertheless, the error found in all cases is $< 0.9\%$ with 20 time steps. Thus, with the MLTBL, the high accuracy results are achieved with as few as 20 time steps.

4.5 SUMMARY

The MLTBL approach is proposed as a numerical options pricing approach for the PFD valuation, where the jump sizes are defined as a priori to choose the jump probabilities to match the characteristic functions. The rationale of the MLTBL approach coincides with the Trigeorgis's (1991) LTBL rationale by extending the one-asset case to the n -assets case. Based on the justification of MLTBL approach's merits with respect to the BEG and NEK approaches, it concludes that MLTBL approach ameliorates the BEG approach in terms of consistency, stability and efficiency. Furthermore, the MLTBL approach also achieves the similar performance as the NEK approach while alleviating NEK's deficiency in maintaining reasonable up- and down-jump sizes.

Table 4-2: Comparisons of efficiency among the BEG, NEK and MLTBL approaches

Parameter values		Case1: $\sigma_1=\sigma_2=\sigma_3=0.2 \quad \rho_{12}=\rho_{13}=\rho_{23}=0.1$					Case2: $\sigma_1=\sigma_2=\sigma_3=0.2 \quad \rho_{12}=\rho_{13}=\rho_{23}=0.7$				
N		10	20	50	100	Analytical	10	20	50	100	Analytical
Eur. max.	MLTBL	2.609	2.623	2.629	2.630	2.631	2.037	2.039	2.041	2.041	2.041
	BEG	2.575	2.603	2.620	2.625		1.926	1.989	2.021	2.031	
	NEK	2.627	2.630	2.631	2.631		2.045	2.042	2.042	2.041	
Eur. call min.	MLTBL	0.284	0.284	0.284	0.284	0.284	0.684	0.689	0.692	0.693	0.694
	BEG	0.271	0.277	0.281	0.282		0.697	0.695	0.694	0.694	
	NEK	0.297	0.282	0.286	0.283		0.700	0.693	0.694	0.693	
Eur. Put min.	MLTBL	0.881	0.885	0.885	0.884	0.884	0.645	0.648	0.651	0.651	0.652
	BEG	0.855	0.869	0.878	0.881		0.615	0.634	0.644	0.648	
	NEK	0.891	0.881	0.887	0.884		0.660	0.653	0.653	0.651	
Parameter values		Case3: $\sigma_1=\sigma_2=\sigma_3=0.1 \quad \rho_{12}=\rho_{13}=\rho_{23}=0.5$					Case4: $\sigma_1=\sigma_2=\sigma_3=0.4 \quad \rho_{12}=\rho_{13}=\rho_{23}=0.5$				
N		10	20	50	100	Analytical	10	20	50	100	Analytical
Eur. max.	MLTBL	1.567	1.567	1.568	1.568	1.568	3.786	3.794	3.798	3.799	3.801
	BEG	1.513	1.542	1.558	1.563		3.668	3.739	3.775	3.788	
	NEK	1.570	1.569	1.569	1.569		3.795	3.799	3.801	3.801	
Eur. call min.	MLTBL	0.537	0.537	0.537	0.537	0.537	0.613	0.617	0.620	0.622	0.623
	BEG	0.521	0.529	0.534	0.535		0.635	0.628	0.625	0.624	
	NEK	0.537	0.535	0.537	0.537		0.623	0.623	0.623	0.623	
Eur. Put min.	MLTBL	0.180	0.178	0.177	0.177	0.177	1.936	1.938	1.939	1.940	1.940
	BEG	0.159	0.168	0.173	0.175		1.869	1.905	1.926	1.933	
	NEK	0.179	0.176	0.177	0.177		1.945	1.944	1.942	1.941	
Parameter values		Case5: $\sigma_1=\sigma_2=\sigma_3=0.2 \quad \rho_{12}=0.8 \quad \rho_{13}=0.6 \quad \rho_{23}=0.3$					Other parameter values: $r = 0.10$ $T = 1.0$ $K = 10.0$ $V_1(t_0) = V_2(t_0) = V_3(t_0) = 10.0$, Note: neg. pr. denotes that the BEG approach leads to negative jump probabilities, namely the stability problem.				
N		10	20	50	100	Analytical					
Eur. max.	MLTBL	2.157	2.157	2.157	2.158	2.158					
	BEG	neg. pr.	neg. pr.	neg. pr.	neg. pr.						
	NEK	2.162	2.159	2.159	2.158						
Eur. call min.	MLTBL	0.579	0.581	0.583	0.583	0.584					
	BEG	neg. pr.	neg. pr.	neg. pr.	neg. pr.						
	NEK	0.587	0.584	0.584	0.584						
Eur. Put min.	MLTBL	0.693	0.694	0.694	0.694	0.694					
	BEG	neg. pr.	neg. pr.	neg. pr.	neg. pr.						
	NEK	0.702	0.696	0.695	0.694						

CHAPTER 5:

HYBRID REAL OPTIONS VALUATION FOR PRODUCT FAMILY DESIGN

A design essentially contains two dimensions: (1) the artifact itself, that is, content of the designed product and (2) the design process through which the artifact is entailed (Jones, 1992). Neely (1998) points out that the management flexibility associated with product development involves two aspects. One is project related, which is referred to as the realization of a project that can be staged, indicating that managers should make a choice between different lines of development. The other is product related, which is referred to as a design realized physically by building in flexibility that enables managers to exercise options. Neely and de Neufville (2001) further argue that the measure for costs and benefits of project design looks very different from the perspective of the design engineer who measure the success in terms of the technological performance, with that from the perspective of the financial analyst focusing on profits in volatile markets. Therefore, a differentiation of the analysis into financial and technical parts is crucial in project design valuation. To achieve an accurate assessment on the value of an investment (for example, a new project or product development), a hybrid method combining the decision analysis with options analysis is proposed by Jiao *et al.* (2006c). The rationality of combining engineering and business decisions in real options valuation for optimal design decisions is also supported by Georgiopoulos et al. (2002).

Under the real options thinking, product family design becomes an optimal decision-making regarding a portfolio of real options to be exercised at different stages of the design project. Naturally, the two aspects: (1) product-related options, referred to as technical real options, and (2) project-related options, referred to as financial real options, involving in the product family design are taken into account. Technical real options characterize the physical flexibility built in the product families that contributes to the technical performance of design. Financial real options, on the other hand, indicate the management flexibility staged along the project life, which constitutes the justification of profit performance for a design. Therefore, the valuation of product family design calls for a hybrid approach combining engineering analysis with financial analysis.

5.1 TECHNICAL REAL OPTIONS

Technical real options are explicitly related to the configuration process of product family design (Du *et al.*, 2001). PFD decision making begins with the selection of a product platform, and then generating product variants by configuring predefined modules within this particular platform. As such, a screening option $x^{SCRE}(\bullet)$, as identified in previous chapter, is introduced. For instance, screening option $x^{SCRE}(PdP_1)$ represents the screening option with regard to product platform PdP_1 .

Corresponding to the basic variety generation methods, four types of primitive configuring options: attaching $x^{ATTA}(\bullet)$, removing $x^{REMO}(\bullet)$, swapping $x^{SWAP}(\bullet)$, and scaling $x^{SCAL}(\bullet)$ respectively are adopted. For the variety nesting operations, a nesting real option $x^{NEST}(\bullet)$ which is a compound of a series of configuring options is applied to a subsystem that consists of multiple differentiation modules. For example, a nesting options $x^{NEST}(x^{REMO}(DM_a)x^{ATTA}(DM_b)x^{SWAP}(DM_c, DM_d))$ represents the

configuration on a subsystem, which is achieved through removing design module DM_a , attaching design module DM_b , and swapping design module DM_c with design module DM_d . The multiplication operators between primitive configuring options indicate the sequence of configuration, which usually follows the subsystem hierarchy from bottom up.

5.2 FINANCIAL REAL OPTIONS

Financial real options are correlated to strategic management of design projects under uncertainty (Neely, 1998). Strategic options analysis deals with the issue of constantly varying discount rates through a process whose net effect is to adjust the project outcomes so that the risk-free rate can be applied. Technically, this process is known as risk-neutral valuation (Hull, 1989). This process requires detailed statistical information on the price and volatility of an asset that is closely related to the project or product at hand. Strategic options related to product development are generally identified as defer/wait, time-to-build, alter, shut-down/abandon, switch and growth options (Lint and Pennings, 2001).

In the context of PFD, four types of financial real options which are coherent with the classical real options are considered: launch, defer, abandon and switch options, denoted as $x^{Lau}(\bullet)$, $x^{Def}(\bullet)$, $x^{Aba}(\bullet)$ and $x^{Swi}(\bullet)$, respectively.

(1) *Launch option.* A launch option $x^{Lau}(\bullet)$ indicates when a design is valuable to be built along the project life,

(2) *Defer option.* A defer option $x^{Def}(\bullet)$ suggests that a design project would be suspended and postponed and resumed in a later time to deal with market uncertainty.

(3) *Abandon option.* An abandon option $x^{Aba}(\bullet)$ allows a design project to be cancelled to deal with the poor market uncertainty.

(4) *Switch option*. A switch option $x^{Swi}(\bullet)$ coincides with flexible changes among different configuration alternatives.

Each financial option treats a technical option as a subproject of investment. For example, a defer option, $x^{Def}(REMO(M_a))$, denotes that a configuration design subproject of removing module M_a has the possibility to be deferred. As a result, the strategic decisions regarding a PFD project is manifested through the analysis of a portfolio of financial real options.

5.3 VALUATION OF TECHNICAL REAL OPTIONS

As reviewed in Chapter 2, design performance measure based on the dollar value is deemed to be difficult in practice. Nevertheless, the ultimate goal of design is to satisfy customer needs (Jones, 1992). Therefore, the value of a technical real options should be measured in terms of customer satisfaction. According to Suh's information axiom (2001), the flexibility value of a design is implied in the measure of information content (i.e. customer satisfaction) by associating functional feature performance as achieved performance range to the customer expected level of performance as target range.

From a customer's viewpoint, the expected performance of design with respect to a particular functional feature, F_{ij} , is described as a utility function, $PU(F_{ij})$, where $PU \in [0,1]$. From the technical viewpoint, the achieved performance, $\tilde{F}_{ij}$, of real options (a design) x_i^T with respect to F_{ij} is described as a probabilistic distribution, $p(\tilde{F}_{ij})$, over the range $[\tilde{F}_{ij}^L, \tilde{F}_{ij}^U]$. As illustrated in Figure 5-1, the achieved performance, $\tilde{F}_{ij}$, of a functional feature is described by a probability density function, $p(\tilde{F}_{ij})$, over the system range, $[\tilde{F}_{ij}^L, \tilde{F}_{ij}^U]$, where $\tilde{F}_{ij}^L$ and $\tilde{F}_{ij}^U$ indicate the lower and upper bounds of the performance respectively. This is achieved by configuring a product platform, that

is, $\tilde{F}_{ij} \leftarrow (PdP_i + \Delta DM_m)$. The expected performance, F_{ij} , covers the design range, $[F_{ij}^L, F_{ij}^U]$ that determines from the configuration requirement with respect to the product platform, i.e., $F_{ij} \leftarrow (BaseSpec + \Delta F_j)$, where F_{ij}^L and F_{ij}^U denote the lower and upper bounds of expected performances, respectively.

Figure 5-1: Correlation of customer expected and design achieved performances

5.3.1 Customer Expected Performance Range

As far as PFD is concerned, a configuration requirement is observed as a ranged specification of a particular functional requirement, i.e., $\Delta F_j \sim [F_{ij}^L, F_{ij}^U]$, and thus can be interpreted as the expected performance of the PFD, that is, F_{ij} . Over this range, customers usually demonstrate different preferences for specific performance values.

Thurston (1991) proposes to construct preference functions based on the utility theory to model customers' preferences over single or multiple product attributes. Chen and Yuan (1999) introduce utility theory based preference functions with regard to a ranged set of functional specification. Such a utility theory based preference measure is applied to describe the varying degree of customer preference for different levels of expected performance. A preference function of the expected performance, $PU(F_{ij})$, is

a function defining the relationship between the degree of preference in terms of utility, u , and a specific level of the expected performance, $\forall F_{ij} \in [F_{ij}^L, F_{ij}^U]$, where F_{ij}^L and F_{ij}^U are the lower and upper bounds of functional feature values, respectively. The preference function is defined in the range of 0 and 1. Full preference (utility) means a fully-acceptable design (performance) and is indicated by $PU = 1$. An unacceptable design (performance) corresponds to no preference (utility), that is, $PU = 0$. In general, the preference function may possess various types of forms and is not limited to a triangular function as shown in Figure 5-1.

5.3.2 Design Achieved Performance Range

PFD may involve in any design parameter changes, $\{\Delta DM_m\}_M$. Most existing research on design configuration focuses on the optimal determination of design parameters and/or their values, in other word, ‘how’ design is to be configured (Simpson, 2004). While the technical details of $\{\Delta DM_m\}_M$ are tedious and always domain dependent, this research emphasizes on the *consequence*, rather than the *content*, of ΔDM_m . Such an understanding coincides with the general principle of performance evaluation in PFD (Chen *et al.*, 1999; Simpson *et al.*, 1998). Further taking into account the uncertainty associated with configuration solutions, PFD is modeled as a probabilistic design process and thus is described ΔDM_m in terms of a probabilistic distribution of the achieved performance of the design, $p(\tilde{F}_{ij})$. To figure out what types of performance distributions, Monte Carlo simulations or other statistical techniques such as Design of Experiments and Response Surface Models can be employed (Siddall, 1983).

5.3.3 Valuation Model

Let $\{F_{ij} | j = 1, \dots, J\}$ be a set of functional features to be fulfilled by a technical real options, $x_i^T \in X^T \equiv \{x_i^T | i = 1, \dots, I\}$. Referring to Suh's original formulation, information content is derived based on the assumption that the probability density functions of the system and design ranges are all uniform (Suh, 2001). This may be not sufficient to assess PFD with different performance behaviors such that $p(\tilde{F}_{ij})$, or the design range assumes different degree of preference, as defined by $PU(F_{ij})$. In this regard, Jiao and Tseng (2004) extend the information content measure to the probability of design success. As illustrated by the shaded areas in Figure 5-1, the probability of design success can be graphically interpreted as the overlap area of $p(\tilde{F}_{ij})$ and $PU(F_{ij})$. By relaxing the assumption of uniform distributions, the calculation of the overlap area can not be replaced with the "common range", $F_{ij}^U - \tilde{F}_{ij}^L$, as used in Suh's original formulation. The joint effect of non-uniform probability density functions over the range, $[\tilde{F}_{ij}^L, F_{ij}^U]$ has to be taken into account.

(1) *Single functional feature.* In the more general case, the information content, I in terms of the probability of success of a functional feature, $P(F_{ij})$, in meeting the expected performance F_{ij} , can be derived from Equation (5-1).

$$I = -\ln P(F_{ij}). \quad (5-1)$$

Mathematically, the probability of success can be defined as the *expected preference function value* of (achieved) design performance over the range of design solutions as shown in Equation (5-2).

$$P(F_{ij}) = \int_{F_{ij}^L}^{F_{ij}^U} PU(F_{ij}) p(\tilde{F}_{ij}) dF_{ij} . \quad (5-2)$$

Theoretically, information content is a cardinal measure, that is $I \in [0, \infty)$, which lacks of indication on the difference in evaluation. For comparisons of different functional features on a common basis, a relative index is preferable which enables absolute boundaries. Therefore, the technical value of real options x_i^T with respect to single functional feature F_{ij} is given as,

$$v_{ij}^T(x_i^T) = \frac{1}{1 - \ln \int_{F_{ij}^L}^{F_{ij}^U} PU(F_{ij}) p(\tilde{F}_{ij}) dF_{ij}} . \quad (5-3)$$

The value of $v_{ij}^T(x_i^T)$ ranges from 0 to 1, where $v_{ij}^T(x_i^T) = 0$ indicates zero degree of customer satisfaction (i.e., no value of real options x_i^T), and $v_{ij}^T(x_i^T) = 1$ suggests the maximum degree of customer satisfaction (and thus the maximal value of real options x_i^T). As a relative measure, $v_{ij}^T(x_i^T)$ represents the relative value of real options x_i^T compared with the maximum amount possible.

Three different technical real options are illustrated in Figure 5-2 where different technical values $v_{ij}^T(x_i^T)$ and a trapezoid preference function are assumed.

Figure 5-2: Implications of technical real options valuation

With technical real options (a), the preference function remains 1 over almost the entire system range and therefore the following technical value is obtained.

$$v_{ij}^T(x_i^T) = \frac{1}{1 - \ln \int_{F_{ij}^L}^{F_{ij}^U} p(\tilde{F}_{ij}) dF_{ij}} \approx 1. \quad (5-4)$$

This is the most desired situation, meaning that the execution of technical real options (a) satisfies customer need exactly. Nevertheless, such value $v_{ij}^T(x_i^T) = 1$ cannot be achieved by technical real options (b) and (c). It is noteworthy that technical real options (c) yields the poorest flexibility in satisfying customer need giving the value $v_{ij}^T(x_i^T) = 0$ and the minimal standard deviation, which indicates the least variability.

(2) *Multiple functional features.* Considering multiple functional features, $\{F_{ij}\}_J$, associated with x_i^T , the probability of success of design corresponding to x_i^T becomes a joint probability. Assume all performance variables are achieved independently; the joint probability is given as,

$$p(\{\tilde{F}_{ij}\}_J) = \prod_{j=1}^J p(\tilde{F}_{ij}). \quad (5-5)$$

Following that the overall value of real options x_i^T with respect to all performance variables, $\{\tilde{F}_{ij}\}_J$, can be obtained as below,

$$V^T(x_i^T) = \frac{1}{1 - \sum_{j=1}^J \ln \int_{F_{ij}^L}^{F_{ij}^U} PU(F_{ij}) p(\tilde{F}_{ij}) dF_{ij}}, \quad (5-6)$$

where $F_{ij} \in [F_{ij}^L, F_{ij}^U], \forall j \in [1, J]$. However, such an independence assumption seldom holds true for most design problems. The correlations among multiple performance variables are dealt with through the valuation of financial real options, to be elaborated in the next Section.

Other than that of a primitive real options, the utility of a compound option (either a nesting or screening option) is derivative based on conjoint analysis (Green and DeSarbo, 1978). First, the utility of each primitive real options is established as partworth utilities through fractional factorial experiments. Then the utility of a compound option is derived from partworth utilities based on regression analysis. For most engineering problems, the performance of design is usually normally distributed (Jiao and Tseng, 2004). Hence, normal distributions are often used to define various achieved performance, $\{p(\tilde{F}_{ij})\}_{I \times J}$. For example, the expected and achieved performances of a screening option are determined at the product platform level. The utility of a product platform results from the aggregation of individual utilities of the constituent CBs of this platform. The design distribution refers to the overall performance of all related CBs.

5.4 VALUATION OF FINANCIAL REAL OPTIONS

5.4.1 Product Demand

The general gist of the real options approach is to deal with the valuation of management flexibility in a constantly changing and uncertain marketplace. Different from the traditional way of financial options in dealing with the sources of uncertainty, real options are more complex and often involve multiple sources of uncertainty and need to handle a mix of private and market-priced risks. Therefore, the sources of uncertainty affecting real options must be identified in a structural way (Amram and Kulatilaka, 1999). Based on the identified and established sources of uncertainty, a mathematical form needs to be developed to express the evolution of an uncertain variable over time in a stochastic process. Allowing the uncertain variable to evolve continuously, a continuous-time stochastic process can be assumed, which is also called

a diffusion process and usually conforms to, for example, a geometric Brownian motion (Pindyck, 1988).

In traditional real options applications, price is identified as the source of uncertainty. In an environment of market competition, a manufacturing firm is indeed passive, rather than as positive as a price maker. Therefore, price should be excluded from the sources of uncertain PFD environment. In practice, the most important factor influencing project decisions is product demand per se. Therefore, the uncertainty in demand is recognized as the main source of uncertainty related to PFD projects.

Consider a configured product from PFD, $y_k \in Y \equiv \{y_k | k = 1, \dots, K\}$. The demand of this product, D_k , is stochastic and follows a geometric Brownian motion (Tannous, 1996). The demand process is thereby written as:

$$dD_k = \mu_k D_k dt + \sigma_k D_k dZ_k, \quad (5-7)$$

where μ_k and σ_k denote the expected rate of demand increase and demand volatility of product y_k , respectively; and $dZ_k = e_k(t)\sqrt{dt}$ refers to the increment of a Wiener process, where $e_k(t) \sim N(0,1)$ is a serially uncorrelated and normally distributed random variable. Between the increments of products y_k and y_l , i.e., dZ_k and dZ_l , there exists a pair-wise correlation coefficient, ρ_{kl} , which is defined as $\rho_{kl}dt = dZ_k dZ_l$.

Based on the real options theory, the mean value of product demand D_k at time t can be determined as the following,

$$E[D_k(t)] = D_k(0)e^{\mu_k t}, \quad (5-8)$$

where $D_k(0)$ denotes the demand of product y_k at current time.

However, assuming the demand to be a continuous process may be unrealistic in practice. For example, the demand for products can only be discrete numbers.

Nonetheless, such an approximation is acceptable when the volume of demand is high enough. Pindyck (1988) assumes that existing assets span stochastic changes in demand. This means that there exists an asset or a portfolio of assets whose price is perfectly correlated with D_k . This is consistent with the assumption that markets are sufficiently complete in that the firm's decisions to invest or produce do not affect the opportunity sets available to investors. Note that if the spanning assumption does not hold true, a capital asset pricing model (CAPM) would not hold true either (Brealey and Myers, 2000). Thus, there should exist an asset or a dynamic portfolio of assets with price A_k that is perfectly correlated with D_k (Constantinides, 1978), and thereby also follows a Brownian motion, that is,

$$dA_k = \alpha_k A_k dt + \sigma_k A_k dz_k. \quad (5-9)$$

The expected rate of demand increase, μ_k , may differ from the drift rate, α_k , which is the equilibrium rate of return, although they have the same covariance as that of the market portfolio. Therefore, the drift rate of the asset, or the dynamic portfolio, has to be adjusted with regard to a factor, often called convenience yield, $\mu_k = \alpha_k - \delta_k$, in order to get the correct value of the option.

5.4.2 Payoff

Let $x_q^F \in X^F \equiv \{x_q^F | q = 1, \dots, Q\}$ denotes a financial real options associated with PFD, may it be a launch, defer, abandon or switch option. Such options can be regarded as ordinary European call options, as the decision rule is that the revenue must exceed the product cost. The payoff from exercising option x_q^F on the expiration date, T , is defined as:

$$v^F(x_q^F, T) = \max \left[\frac{A_q^F}{C_q^F} D_k, 0 \right], \quad (5-10)$$

where A_q^F is the price of option x_q^F , C_q^F is the cost incurred if enacting option x_q^F , and D_k is the demanded quantity of product y_k that requires option x_q^F . In the context of PFD, the price of a financial real options x_j^F is defined as the total value of all technical real options, $\{x_i^T | i = 1, \dots, I_q\}$, operated by x_q^F , that is, $A_q^F = \sum_{i=1}^{I_q} V^T(x_i^T)$. Likewise, the cost estimate of financial options x_q^F is defined as the total cost of all technical real options, $\{x_i^T\}_{I_q}$, operated by x_q^F , that is, $C_q^F = \sum_{i=1}^{I_q} C^T(x_i^T)$, where $C^T(x_i^T)$ is the specific cost measure of each individual technical option x_i^T .

In addition, modeling the payoff as a ratio of technical value and cost coincides with the consensus on customer perceived values in marketing – the customer's expectation of product quality in relation to the actual amount paid for it. It also excels in maintaining a consistent measure for the relative comparison of various alternatives on a common ground, whilst avoiding the intricate pricing problem. This is consistent with the findings reported by Choi and DeSarbo (1994) – “exact cost estimates are not necessary as long as the relative magnitudes are in order.”

5.4.3 Cost

Since traditional cost structures may not hold well with product families (Yano and Dobson, 1998), the cost measure of a technical option is determined based on standard time estimation and variation in the process capability (Jiao and Tseng, 2004). Considering the one-side specification limit, the cost measure of x_i^T is given in Equation (5-11) and depicted in Figure 5-3.

$$C^T(x_i^T) = \frac{3\sigma_i^T}{USL_i^T - \mu_i^T}, \quad (5-11)$$

where USL_i^T , μ_i^T , and σ_i^T are the upper specification limit, the average, and the standard deviation of the estimated cycle time of x_i^T , respectively.

Variations in the cycle time are characterized by μ_i^T and σ_i^T , reflecting the compound effect of PFD on production in terms of process variations. The USL_i^T can be determined based on the worst case analysis of a given process platform, whereby generic routings are always used to accommodate various product variants configured from the corresponding product platform (Jiao *et al.*, 2005). In practice, efforts in standard time study can also contribute to the evaluation of USL_i^T . The introduction of $C^T(x_i^T)$ facilitates the evaluation of process variation in terms of cycle time performance. As there is a positive correlation between costs and the cycle time, this measure gives an indication of the level of expenses required to implement particular configuration in production. Modeling the economic latitude of PFD through cycle time and process variation performance can alleviate the difficulties in traditional cost estimation which turns to be tedious and less accurate.

Figure 5-3: Implications of cost measure

The value of $C^T(x_i^T)$ ranges from 0 to 1, where a large value suggests the related production is easy or cheap, else reflects the production is expensive or difficult. The $C^T(x_i^T)$ for three different processes of configuration are illustrated in Figure 5-3. While σ_i^T measures the spread of the process in regard to the specification range, μ_i^T indicates the offset from the target. Processes (a) and (b) possess the same σ_i^T yet different μ_i^T ($\mu_{(a)}^T < \mu_{(b)}^T$), and thus process (a) has better value, that is, $C^T(x_{(b)}^T) < C^T(x_{(a)}^T) < 1$. Processes (b) and (c) possess the same μ_i^T yet different σ_i^T ($\sigma_{(b)}^T > \sigma_{(c)}^T$), thus $C^T(x_{(b)}^T) < C^T(x_{(c)}^T) < 1$, suggesting process (c) is less expensive.

According to the conditions of one-side specification limits for a ‘smaller the better’ type quality characteristic, the process yield can be inferred:

$$\%Yield = F_i(USL). \quad (5-12)$$

Under normal conditions, the index exhibits a one-to-one relationship with the process yield. The relationship is given by,

$$\%Yield = \Phi(3C^T(x_i^T)), \quad (5-13)$$

where Φ is the cumulative distribution function for a standard normal distribution. As a result, the $C^T(x_i^T)$ directly reflects the process yield because the process yield increases as the $C^T(x_i^T)$ increases. For example, for a 84.134% process yield, $C^T(x_i^T) = 1/3$; and for a 99.865% process yield, $C^T(x_i^T) = 1.0$.

5.4.4 Pricing Model

The pricing of options generally depends on the value of several underlying variables and can thereby be seen as a derivative. The value of a derivative can be

expressed as certain analytical formulas, such as the Black-Scholes formula (Trigeorgis, 1996). The financial real options associated with PFD, however, possess a complex payoff pattern and are dependent on several underlying assets. The value of financial real options is thus dependent on multivariate underlying assets represented by the demand of each product. Based on the options theory (Trigeorgis, 1996), the value of a real options x_q^F must satisfy the following partial differential equation:

$$\frac{\partial V^F(x_q^F)}{\partial t} + \sum_{k=1}^K (r - \delta_k) D_k \frac{\partial V^F(x_q^F)}{\partial D_k} + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^L \rho_{kl} \sigma_k \sigma_l D_k D_l \frac{\partial^2 V^F(x_q^F)}{\partial D_k \partial D_l} - r V^F(x_q^F) = 0, \quad (5-14)$$

where $V^F(x_q^F)$ denotes the value of x_q^F and r is a risk-free rate. Because the terminal boundary conditions are very complex, it is difficult to obtain an analytical solution to the above expression. There are two types of numerical approaches available: a lattice approach, which also allows for American options, and Monte Carlo simulation, which is restricted to European options.

This research adopts a multivariate binomial lattice approach to the pricing of financial options of PFD. If a lattice approach is used in the case of K product variants, demand at each end node at time T together with prices and cost estimates can be used to find an optimal configuration at each end node. Then, using the risk-neutral probabilities and the risk-free rate, the value of the option at the valuation date can be estimated by working backward in the lattice. The detailed multivariate binomial lattice procedure can be referred to Chapter 4.

5.5 PRODUCT FAMILY DESIGN OPTIMIZATION

With PFD real options, configuration design becomes the selection of specific technical real options along with their relevant financial real options. Given a customer order expressed as a set of customer needs, $\{CN_m | m = 1, \dots, M\}$, a few product variants,

$\{y_k\}_K$, may be configured from existing product platforms. Each configured product, y_k , is achieved through a portfolio of call options, including a subset of existing technical real options, $X_{y_k}^T \equiv \{x_{y_k}^T | r=1, \dots, R_{y_k} < I\} \subset \{x_i^T\}_I$, and a subset of available financial real options, $X_{y_k}^F \equiv \{x_{y_k}^F | s=1, \dots, S_{y_k} < Q\} \subset \{x_q^F\}_Q$. The performance variables of each technical real option $s x_r^T$ originate from a subset of original customer needs, i.e., $\{\tilde{F}_{ij} | j=1, \dots, J_r\} \subset \{CN_m\}_M$. The objective of PFD is to achieve the overall optimization of the selected portfolio of real options. Therefore, the expected payoff of product y_k is subjected as the objective function, which is defined as:

$$\mathbf{Max} \ E[V(y_k)] = V^T(X_{y_k}^T) V^F(X_{y_k}^F) = \sum_{r=1}^{R_{y_k}} V^T(x_r^T) \sum_{s=1}^{S_{y_k}} V^F(x_s^F), \quad (5-15)$$

where $V(y_k)$ is the payoff function defined for product y_k , $V^T(x_r^T)$ suggests the technical value of a technical real options involved in y_k according to Equation (5-6), and $V^F(x_s^F)$ indicates the financial value of a financial real options associated with y_k , which is calculated according to Equations (5-10), (5-11), and (5-14) using the multivariate binomial lattice approach. The PFD optimization problem is summarized in Table 5-1.

Table 5-1: Product family design optimization model

Given:	Customer needs : $\{CM_m\}_M, \{PU(CN_m)\}_M, \{(CN_m^L, CN_m^U)\}_M$. Technical real options : $\{x_i^T\}_I, \{p(\tilde{F}_{ij})\}_{I \times J}, \{C^T(x_i^T)\}_I$. Financial real options : $\{x_q^F\}_Q, \{D_k\}_K, r, \{u_k\}_K, \{\sigma_k\}_K$. Process platform model: $\{\mu_i^T\}_I, \{\sigma_i^T\}_I, \{USL_i^T\}_I$.
Find:	An optimal portfolio of real options for y_k : $y_k \sim (\{x_r^T\}_R, \{x_s^F\}_S)$.
Satisfy:	$\max E[V(y_k)] = \sum_{r=1}^{R_{y_k}} V^T(x_r^T) \sum_{s=1}^{S_{y_k}} V^F(x_s^F)$.
Subject to:	Configuration constraints Capacity constraints

Figure 5-4 provides an illustration of hybrid real options involved under PFD valuation in the Bill-of-Materials (BOM) structure. Overall hybrid real options valuation for PFD discussed above is summarized in the valuation flow diagram as shown Figure 5-5.

Figure 5-4: Involvement of hybrid real options under product family design valuation

Figure 5-5: Flow diagram of hybrid valuation for product family design

Conducting the conjoint-based search for an optimal portfolio of real options always results in combinatorial optimization problems due to typically discrete functional feature values used in the configuration. Nearly all of these problems are known to be mathematically intractable or NP-hard, and thus mainly heuristic solution procedures have been proposed for the various problem types. Conventional enumeration-based optimization techniques become inhibitive given that the number of possible combinations may be enormous. Hence, genetic algorithms (GA) are introduced, which have been proven to excel in searching for the optimal combination. The details of GA and its implementation for PFD are elaborated in the next chapter.

5.6 CASE STUDY

5.6.1 Background

The proposed hybrid PFD framework is verified at an electronics company producing mass customized vibration motors for mobile phones. In order to meet diverse customer needs related to mobile phones, the design and production of vibration motors are typically custom built, resulting in an exponentially increased number of product and process variety.

The production environment of the company is a combination of assemble to order and make to order, wherein a number of common standard components have been kept in stock and the design and production of vibration motors does not start until customer orders are received.

While the external business environment is characterized by rapidly changing and unpredictable product demands, the internal manufacturing environment is facing the challenge of diverse custom designs and enormous variations in production planning. To alleviate the difficulties in engineering change control and the recurrence problem

related to frequent process variations, the company adopts the strategy of developing product and process platforms to support product family design. Without losing illustrative completeness, the examples reported here are simplified data based on the company's practice of PFD.

The standard functional features consist in a vibration motor is shown in Table 5-2. Based on the analysis of historical data on the company's product fulfillment and current manufacturing capabilities, the vibration motor product platform is constructed and accordingly the associated standard routings are identified.

Table 5-2: Standard functional features of vibration motor

Module	Functional Feature $\{CN_m\}_M$
Armature (A)	A1 (Current / mA)
	A2 (Pb free)
Frame (F)	F1 (Length / mm)
	F2 (Diameter / mm)
Bracket (B)	B1 (Color)
	B2 (Connected Method)
	B3 (Coating)
Weight (W)	W1 (Shape)
	W2 (Holding Strength / kg)
	W3 (Speed / rpm)
Magnet (M)	M1 (Pb free)
Rubber Holder (RH)	RH1 (Color)
	RH2 (Shape)

Table 5-3 summarizes the specifications of product platforms established; there are PdP_1 and PdP_2 to target various vibration motor market segments. For verifying purpose, two customer orders are chosen: CNA and CNB, which represent low- and high-end customer needs, respectively. The specifications of individual customer needs, as well as, the product demand distributions in the respective markets are given in Table 5-4. Each product platform supports a class of product family design.

Table 5-3: Specifications of product platforms for market segments

Functional Feature $\{CN_m\}_M$	Product Platform (Customer Needs per Market Segment) $[F_{iq}^L, F_{iq}^U] \& u(F_{iq})$	
	PdP ₁	PdP ₂
A1	[50, 70] / Triangular	[85, 110] / Triangular
A2	[Y, N] / Uniform	[Y, N] / Uniform
F1	[8.5, 12] / Triangular	[14, 17] / Triangular
F2	[6.5, 15] / Triangular	[15, 27] / Triangular
B1	[R, W, B] / Uniform	[R, B, G] / Uniform
B2	[U, X, L] / Uniform	[U, M, T] / Uniform
B3	[Y, N] / Uniform	[Y, N] / Uniform
W1	[P, T] / Uniform	[P, T, U] / Uniform
W2	[2.5, 5] / Triangular	[5.5, 8.5] / Triangular
W3	[5000, 9200] / Triangular	[9500, 14000] / Triangular
M1	[Y, N] / Uniform	[Y, N] / Uniform
RH1	[R, W, B] / Uniform	[R, B, G] / Uniform
RH2	[P, T] / Uniform	[P, T, U] / Uniform

Table 5-4: Specifications of individual customer needs for CNA and CNB

Functional Feature $\{CN_m\}_M$		Individual Customer Needs $[CN_m^L, CN_m^U] \& u(CN_m)$	
		Customer CNA	Customer CNB
A1		60±15 / Triangular	80±20 / Triangular
A2		N / Uniform	Y / Uniform
F1		9.5±3 / Triangular	13.5±4 / Triangular
F2		10±4.5 / Triangular	19±8 / Triangular
B1		R / Uniform	B / Uniform
B2		U / Uniform	M / Uniform
B3		N / Uniform	Y / Uniform
W1		P / Uniform	U / Uniform
W2		4±2.5 / Triangular	5±3 / Triangular
W3		5500±200 / Triangular	10500±1500 / Triangular
M1		N / Uniform	Y / Uniform
RH1		R / Uniform	B / Uniform
RH2		P / Uniform	T / Uniform
Product Demand	Increase Rate μ_{CN}	1%	5%
	Volatility σ_{CN}	0.1	0.45
	Initial Demand $D_{CN}(0)$	15000	950

For example PdP₁, as illustrated in Figure 5-6, establishes the configuration mechanism whereby product variants are generated by configuring options of variety generation on top of those common modules of the product architecture.

Figure 5-6: Variety generation within platform PdP_1

In accordance with the identified variety generation methods, PFD real options are defined for PdP_1 , as shown in Table 5-5.

Table 5-5: Real options associated with the PdP_1 family

ID	Technical Real Options $\{x_i^T\}_I$	Financial Real Options $\{x_q^F\}_Q$
A	$x^{REMO}(M_{a11})$	$x^{Lau}(A), x^{Def}(A), x^{Aba}(A), x^{Swi}(A).$
B	$x^{ATTA}(M_{anew})$	$x^{Lau}(B), x^{Def}(B), x^{Aba}(B), x^{Swi}(B).$
C	$x^{SWAP}(M_{a11}, M_{a12})$	$x^{Lau}(C), x^{Def}(C), x^{Aba}(C), x^{Swi}(C).$
D	$x^{SWAP}(M_{f11}, M_{f12})$	$x^{Lau}(D), x^{Def}(D), x^{Aba}(D), x^{Swi}(D).$
E	$x^{SWAP}(M_{f21}, M_{f22})$	$x^{Lau}(E), x^{Def}(E), x^{Aba}(E), x^{Swi}(E).$
F	$x^{SWAP}(M_{f1}, M_{f2})$	$x^{Lau}(F), x^{Def}(F), x^{Aba}(F), x^{Swi}(F).$
G	$x^{SWAP}(M_{b21}, M_{b22})$	$x^{Lau}(G), x^{Def}(G), x^{Aba}(G), x^{Swi}(G).$
H	$x^{SWAP}(M_{w11}, M_{w12})$	$x^{Lau}(H), x^{Def}(H), x^{Aba}(H), x^{Swi}(H).$
I	$x^{REMO}(M_{w21})$	$x^{Lau}(I), x^{Def}(I), x^{Aba}(I), x^{Swi}(I).$
J	$x^{ATTA}(M_{w2new})$	$x^{Lau}(J), x^{Def}(J), x^{Aba}(J), x^{Swi}(J).$
K	$x^{SWAP}(M_{w21}, M_{w22})$	$x^{Lau}(K), x^{Def}(K), x^{Aba}(K), x^{Swi}(K).$
L	$x^{SWAP}(M_{w31}, M_{w32})$	$x^{Lau}(L), x^{Def}(L), x^{Aba}(L), x^{Swi}(L).$
M	$x^{SWAP}(M_{w1}, M_{w2})$	$x^{Lau}(M), x^{Def}(M), x^{Aba}(M), x^{Swi}(M).$
N	$x^{SCRE}(PdP_1)$	$x^{Lau}(N), x^{Def}(N), x^{Aba}(N), x^{Swi}(N).$
HK	$x^{NEST}(x^{SWAP}(M_{w11}, M_{w12})x^{SWAP}(M_{w21}, M_{w22}))$	$x^{Lau}(HK), x^{Def}(HK), x^{Aba}(HK), x^{Swi}(HK).$
HL	$x^{NEST}(x^{SWAP}(M_{w11}, M_{w12})x^{SWAP}(M_{w31}, M_{w32}))$	$x^{Lau}(HL), x^{Def}(HL), x^{Aba}(HL), x^{Swi}(HL).$
KL	$x^{NEST}(x^{SWAP}(M_{w21}, M_{w22})x^{SWAP}(M_{w31}, M_{w32}))$	$x^{Lau}(KL), x^{Def}(KL), x^{Aba}(KL), x^{Swi}(KL).$

The specification of each technical real options of PdP_1 and the corresponding process data are shown in Table 5-6. As far as platform PdP_1 is concerned, 1 screening real options, 13 primitive technical real options and 3 nesting real options are identified.

Considering four types of financial real options in relation to each technical real options, the total number of financial real options for platform PdP₁ is 68. Likewise, the total numbers of real options associated with PdP₂ are identified as 16 as shown and listed in Figure 5-7 and Table 5-7, respectively. This gives rise to 64 financial real options for PdP₂.

Table 5-6: Specifications of technical real options and their process performances
within PdP₁ family

Technical Option, $\{x_i^T\}_I$		Technical Performance		Process Performance		
		$\{\tilde{F}_{ij}\}_J$	$[\tilde{F}_{ij}^L, \tilde{F}_{ij}^U] / p(\tilde{F}_{ij})$	μ_i^T	σ_i^T	USL_i^T
Primitive Options	A	A1	[50, 70] / Triangular	26.3	9.5	47.5
		A2	[Y, N] / Uniform			
	B	A1	[45, 100] / Triangular	28.7	6.8	56.4
	C	A1	[85, 110] / Triangular	22.3	7.3	40.1
	D	F1	[14, 17] / Triangular	11.6	8.4	32.1
	E	F2	[15, 27] / Triangular	15.5	6.3	22.3
	F	F1	[14, 17] / Triangular	78.6	18.1	114.5
		F2	[15, 27] / Triangular			
		M1	[Y, N] / Uniform			
	G	B2	[U, M, T] / Uniform	14.6	7.8	21.2
	H	W1	[P, T, U] / Uniform	17.4	7.4	23.2
	I	W1	[P, T, U] / Uniform	35.5	5.2	65.0
		W2	[1.5, 6.5] / Triangular			
		W3	[5000, 9200] / Triangular			
	J	W2	[1.5, 10] / Triangular	10.8	4.45	17.7
	K	W2	[5.5, 8.5] / Triangular	8.5	2.3	11.8
	L	W3	[9500, 14000] / Triangular	15.6	7.15	27.6
	M	W1	[P, T, U] / Uniform	64.8	16.2	105.9
		W2	[5.5, 8.5] / Triangular			
		W3	[9500, 14000] / Triangular			
		RH1	[R, W, B] / Uniform			
		RH2	[P, T] / Uniform			
	N	Specifications of PdP ₁ in Table 5-2		447.9	76.5	555.0
Compound Options	HK	W1	[14, 17] / Triangular	25.0	7.5	42.7
		W2	[15, 27] / Triangular			
	HL	W1	[14, 17] / Triangular	31.5	8.7	51.3
		W3	[9500, 14000] / Triangular			
	KL	W2	[15, 27] / Triangular	32.4	9.8	50.0
		W3	[9500, 14000] / Triangular

Figure 5-7: Variety generation within platform PdP₂

Table 5-7: Real options associated with the PdP₂ family

ID	Technical Real Options $\{x_i^T\}_I$	Financial Real Options $\{x_q^F\}_Q$
A	$x^{REMO}(M_{a12})$	$x^{Lau}(A), x^{Def}(A), x^{Aba}(A), x^{Swi}(A).$
B	$x^{ATTA}(M_{a1new})$	$x^{Lau}(B), x^{Def}(B), x^{Aba}(B), x^{Swi}(B).$
C	$x^{SWAP}(M_{f12}, M_{f11})$	$x^{Lau}(C), x^{Def}(C), x^{Aba}(C), x^{Swi}(C).$
D	$x^{REMO}(M_{f12})$	$x^{Lau}(D), x^{Def}(D), x^{Aba}(D), x^{Swi}(D).$
E	$x^{ATTA}(M_{f1new})$	$x^{Lau}(E), x^{Def}(E), x^{Aba}(E), x^{Swi}(E).$
F	$x^{SWAP}(M_{f22}, M_{f21})$	$x^{Lau}(F), x^{Def}(F), x^{Aba}(F), x^{Swi}(F).$
G	$x^{REMO}(M_{f22})$	$x^{Lau}(G), x^{Def}(G), x^{Aba}(G), x^{Swi}(G).$
H	$x^{ATTA}(M_{f2new})$	$x^{Lau}(H), x^{Def}(H), x^{Aba}(H), x^{Swi}(H).$
I	$x^{SWAP}(M_{f2}, M_{f1})$	$x^{Lau}(I), x^{Def}(I), x^{Aba}(I), x^{Swi}(I).$
J	$x^{REMO}(M_{w22})$	$x^{Lau}(J), x^{Def}(J), x^{Aba}(J), x^{Swi}(J).$
K	$x^{ATTA}(M_{w2new})$	$x^{Lau}(K), x^{Def}(K), x^{Aba}(K), x^{Swi}(K).$
L	$x^{SWAP}(M_{w32}, M_{w31})$	$x^{Lau}(L), x^{Def}(L), x^{Aba}(L), x^{Swi}(L).$
M	$x^{SCRE}(PdP_2)$	$x^{Lau}(M), x^{Def}(M), x^{Aba}(M), x^{Swi}(M).$
CF	$x^{NEST}(x^{SWAP}(M_{f12}, M_{f11})x^{SWAP}(M_{f22}, M_{f21}))$	$x^{Lau}(CF), x^{Def}(CF), x^{Aba}(CF), x^{Swi}(CF).$
DEGH	$x^{NEST}\left(x^{REMO}(M_{f12})x^{ATTA}(M_{f1new})\right)$ $x^{REMO}(M_{f22})x^{ATTA}(M_{f2new})$	$x^{Lau}(DEGH), x^{Def}(DEGH), x^{Aba}(DEGH), x^{Swi}(DEGH).$
JKL	$x^{NEST}(x^{REMO}(M_{w22})x^{ATTA}(M_{w2new})x^{SWAP}(M_{w32}, M_{w31}))$	$x^{Lau}(JKL), x^{Def}(JKL), x^{Aba}(JKL), x^{Swi}(JKL).$

5.6.2 Hybrid Valuation of Product Families

For customer CNB, the GA procedure terminates at the 299th generation, as shown in Figure 5-8, with a return of near-optimal design that achieves an expected payoff of 711.63K. The details of the optimal design for customer CNB are given in Table 5-8.

Figure 5-8: Maximal expected payoffs for customer CNB among generations

Table 5-8: Product family design solution for customer CNB at the 299th generation

Platform	PdP ₂
Common Modules (CBs)	m _{a2} , m _{a22} , m _{b2} , m _{b12} , m _{b22} , m _{b32} , m _{w2} , m _{w12} , m _{w32} , m _{m2} , m _{m12} , m _{rh2} , m _{rh12} , m _{rh22} .
Differentiation Module (DEs)	m _{a12} , m _{t2} , m _{f12} , m _{f22} , m _{w22}
Technical Option $\left\{ \begin{matrix} x_r^T \\ x_s^F \end{matrix} \right\}_{R_y}$	$x^{SCRE}(PdP_2), x^{REMO}(M_{a12}), x^{REMO}(M_{w22}), x^{ATTA}(M_{w2new}),$ $x^{NEST} \left(x^{REMO}(M_{f12}) x^{ATTA}(M_{f1new}) x^{REMO}(M_{f22}) x^{ATTA}(M_{f2new}) \right).$
Financial Option $\left\{ \begin{matrix} x_r^T \\ x_s^F \end{matrix} \right\}_{S_y}$	$x^{Lau}(M), x^{Def}(M), x^{Aba}(M), x^{Swi}(M), x^{Lau}(A), x^{Def}(A), x^{Aba}(A), x^{Swi}(A), x^{Lau}(J),$ $x^{Def}(J), x^{Aba}(J), x^{Swi}(J), x^{Lau}(K), x^{Def}(K), x^{Aba}(K), x^{Swi}(K), x^{Lau}(DEGH), x^{Def}(DEGH),$ $x^{Aba}(DEGH), x^{Swi}(DEGH).$
Expected Payoff $E[V(\hat{y})]$	711.63K

(1) *Technical Performance among Individual Designs.* Figure 5-9 compares the results of the technical value achieved for customer CNB among generations. It is interesting to observe that the distribution of technical performance does not tally with that of the fitness shown in Figure 5-8. The optimal solution (i.e., the last generation) does not produce the maximal technical value. On the other hand, a number of high technical value achievements do not correspond to high fitness. Likewise, as shown in Figure 5-10, the distribution of cost performance among generations disorders the pattern of fitness distribution shown in Figure 5-9. This may illustrate the fact that a high technical achievement is usually accompanied with a high cost to incur. Therefore,

the expected payoff is a more reasonable fitness measure, than the technical value, to model tradeoffs between design performance and the cost.

Figure 5-9: Achieved technical values for customer CNB among generations

Figure 5-10: Cost performance of optimal designs for customer CNB among generations

Figure 5-11 compares the achievements, in terms of the normalized expected payoff, technical value and cost of top 3 product designs for customer CNB in the 299th generation that returns the optimal solution. Among these designs in the population, two ($\hat{y}_1^{CNB}$ and $\hat{y}_2^{CNB}$) are derived from platform PdP₂, whereas $\hat{y}_3^{CNB}$ is based on platforms PdP₁. Obviously, in terms of an overall satisfaction of CNB, those designs derived from product platform PdP₂ outperform product platform PdP₁.

It is interesting to notice that the peak of technical achievement ($\hat{y}_2^{CNB}$) does not contribute to producing the best fitness as its cost is estimated to be high. On the other hand, the minimum cost measure ($\hat{y}_3^{CNB}$) does not mean the best achievement of overall performance measure as its technical performance is moderate. Also interesting to

observe is that, within the same platform, the worst fitness ($\hat{y}_3^{CNB} @ PdP_1$) may not perform with the highest cost figure (it is $\hat{y}_2^{CNB} @ PdP_2$ instead). Likewise, the highest technical achievement ($\hat{y}_2^{CNB} @ PdP_2$) may not correspond to the best fitness (it is $\hat{y}_1^{CNB} @ PdP_2$ instead). The best design ($\hat{y}_1^{CNB} @ PdP_2$) results from a leverage of both technical and cost performances.

Figure 5-11: Performance comparison of optimal design population for customer CNB

Similar phenomenon as discussed above on the optimal design population for customer CNB is found while comparing the performances of optimal design population for customer CNA. The illustration of the performances comparison of optimal design population for CNA is given in Figure 5-12, whereby the optimal design population $\hat{y}_1^{CNA}$ has resulted into the best leverage on both technical and cost performances within the platform PdP₁.

Figure 5-12: Performance comparison of optimal design population for customer CNA

5.7 SUMMARY

This chapter develops the hybrid real options valuation framework to evaluate PFD. Integrating the engineering and financial analyses, the valuation procedure clearly recognizes the value of management control and the exercise of choices at key decision points along the PFD project life. It permits a consistent choice of the risk-free discount rate for the valuation, because the project risks can be diversified and the market risks are accounted for by the options analysis.

CHAPTER 6:

A HYBRID GENETIC ALGORITHM FOR PRODUCT FAMILY DESIGN

Reaching for an optimal portfolio of real options has always been characterized as combinatorial optimization problems. As an increasing number of functional features have engaged in PFD, the multi-feature product variants represented by different real options combinations have thus become economically and technologically infeasible. Such problems are usually known to be mathematically intractable or NP-hard where one fails to notice the generation efficiency for solutions. Therefore, heuristic solution procedures are proposed to adapt to various problem types. Comparing with traditional calculus-based or approximation optimization techniques, genetic algorithms (GA) have been proven to excel at solving combinatorial optimization problems (Steiner and Hruschka, 2002). As a wide variety of configurations of real options for specific product variants are involved in the PFD optimization, a simple algorithm is often not expected to exhibit extraordinary performance. To implement the hybrid real options valuation framework proposed in the previous chapter, a hybrid GA-based (HGA) approach is exploited in this study.

6.1 GENETIC ALGORITHMS

A number of methods and algorithms have been developed to solve combinatorial optimization problems. Sait and Youssef (1999) have divided them into two groups: exact and approximation algorithms. As far as the enumerative nature is concerned,

exact algorithms are not easy to design with moderate computational effort as can be seen from the complexity theory (Garey and Johnson, 1979).

A major trend in solving such hard problems is to utilize an effective heuristics search (Kamrani and Gonzalez, 2003). In recent studies, some meta-heuristics such as multi-start local search (Houck *et al.*, 1996), simulated annealing (Kirkpatrick *et al.*, 1982), tabu search (Glover, 1993) and genetic algorithms (Holland, 1992) had been commonly adopted. Reeves (1993) and Aarts and Lenstra (1997) have reported a thorough survey of these approaches to commonly defined combinatorial problems. A dynamic-programming heuristic method has been developed by Kohli and Sukumar (1990). Nair *et al.* (1995) have developed a beam search heuristic method and performed a computational study of the beam search method and the dynamic programming heuristic method.

Based on an extensive comparative computational study, Alexouda (2004) has found that the evolutionary algorithms are close to optimal and, in most cases, the GA obtains a better solution than that found by the beam search method. The GA approach adopts a probabilistic search technique based on the principle of natural selection by survival of the fittest and merely uses objective function information, and thus is easily adjustable to different objectives with little algorithmic modification (Holland, 1992). However, GA is in general incapable of fine-tuning for obtaining the global optimum (Houck *et al.*, 1996). As a result, various modifications have been done by incorporating local search techniques into the evolution process for particular problems (Renders and Flasse, 1996; Chu and Beasley, 1997).

6.2 GENETIC ALGORITHMS FOR PRODUCT FAMILY DESIGN

Under PFD optimization, it has involved a wide variety of configurations of the technical and financial real options. Such conjoint-based search for an optimal portfolio

of real options always results in combinatorial optimization problems due to typical values of either primitive or compound technical real options, which are derived from the conjoint analysis (Kaul and Rao, 1995). Thus, the employment of HGA allows an efficient convergence of optimal solution (real options portfolios) which is constructed directly from part-worth utility of functional features (primitive real options) or modules (compound real options)(Jiao *et al.*, 2006). Furthermore, with the complications inherent in the PFD, either a specific or universally applicable GA has the difficulties in dealing with those issues. The noteworthy issues are elaborated below.

(1) *Complexity of product family data.* Instead of a collection of individual product variants, the organization of product family data needs to explicate the relationships between variants. That is to deal with the product family rather than individual variants. Moreover, PFD is valued from both the financial and the technical perspectives. Such hybrid valuation on PFD thereby should be represented in terms of customer needs, optimal real options portfolio (optimal PFD), financial and technical real options subsets, compound real options (subassemblies), and primitive real options (functional features), as well as, the correlations among multiple performance variables. As correspondence to the PFD configuration, the technical valuation is undertaken by propagating along the product structure explored through explosion of the bill-of-materials (BOM).

The vast and complex valuation on PFD optimization institutes multiple real options at various modules configurations and a large number of real options portfolios, and thus diverse individual configuration spaces need to be explored. Traditionally, a problem-specific encoding scheme is undertaken to deal with a particular configuration space, where a unique optimization model is formulated. An example of the complexity of using a problem-specific GA for two distinct PFD cases is illustrated in Figure 6-1

where each GA-based PFD case is treated as a separate process.

As a result, traditional GA has difficulties in distinguishing configuration spaces and is not reusable in various configuration cases. Therefore, both the objective models and chromosome representation schemes need to be modified to adapt to the varied problem when configuration spaces change their contents according to diverse customer needs.

Figure 6-1: Problem-specific genetic algorithms for product family design

(2) *Constraint handling*. There are mainly two types of constraints involved in PFD: configuration constraints and selection constraints (Du *et al.*, 2001). Configuration constraints refer to the restrictions on choices of technical real options with respect to customer perceived utility, customer satisfaction, and process efficiency. Generally, configuration constraints are described as IF THEN rules. Selection constraints, on the other hand, refer to the customer's expectation of product quality in relation to the payoff of PFD to be paid. Although a universally applicable GA based on universal encoding may be adapted to diverse PFD scenarios, real problems are too complex to allow direct encoding, where the original solution of a given problem is represented by the chromosome as a whole (Gen and Cheng, 1997). For such complex problems as PFD, a universally applicable GA often yields infeasible offspring due to the ineffectiveness in constraint handling (Kamrani and Gonzalez, 2003).

In overcoming the above issues, HGA is integrated to enable diverse configuration

spaces by making use of a generic encoding strategy that originates from the generic PFD optimization model. The use of the HGA for PFD is far more straightforward compared to the traditional GA. The complexity of using the HGA is exhibited in Figure 6-2 where the HGA-based PFD cases follow a common process.

Figure 6-2: Hybrid genetic algorithm for product family design

6.3 A HYBRID FRAMEWORK

By executing the outstanding features offered in the HGA, HGA-based PFD is modeled and formulated according to the following procedures as depicted in Figure 6-3.

Figure 6-3: Procedures of hybrid genetic algorithm

6.3.1 Configuration Space Formulation

In response to specific customer needs, it is necessary to develop diverse configuration spaces. Figure 6-4 shows a configuration space which is represented as an AND/OR graph. It is established as a hierarchical structure where a number of feasible PFD alternatives (real options portfolios), modules (compound real options), candidates (primitive real options), functional features, design parameters, and their relationships are described within a single formalism.

Figure 6-4: A configuration space

The configuration space is composed of K PFD alternatives, each of which is configured by J modules. Each module contains a number of available candidates, among which only one can be chosen for final solutions. Each candidate is assumed to contain a number of functional features and their corresponding design parameters. By constructing the configuration space along the hierarchical structure, PFD configuration can be identified and encoded easily using the nodes and leaves instead of the real parts, thus providing a concise way of “combination” for improving the efficiency of optimization.

6.3.2 Generic Encoding

A generic encoding is able to characterize variation of configuration spaces and diverse PFD. The basic concern of generic encoding is the representation of a PFD optimization problem to be solved with a finite-length string called chromosome. Figure 6-5 shows an example of the generic encoding. A generic encoding strategy (Jiao *et al.*, 2006a) is undertaken to represent the configuration of a product variant from existing real options and product platforms.

Figure 6-5: An illustration of generic encoding

A configuration is represented by a chromosome consisting of a string, which is divided into two fragments. Both the fragments of chromosome (i.e., substring) represent the overall technical and financial real options involved in the PFD respectively. Each element of the string, called gene, indicates a compound real options. The value assumed by a gene, called allele, represents an index of the specific primitive real options involved in a module variant. A valid real options portfolio configuration (chromosome) consists of one to many selected real options (fragments of chromosome), exhibiting a type of composition (AND) relationships. Likewise, each type of real options (fragment of chromosome) comprises more than one instance

(genes). Nevertheless, each instance (gene) can assume one or many out of all the possible primitive real options (alleles) for specific module variants, suggesting an exclusive all (XOR) instantiation.

The format of an allele may be either a binary or integer number (Holland, 1992). The binary format is the most general form widely used for modeling the binary-selection type of problems (Gen and Cheng, 2000). For the case of PFD, the integer format is adopted for representing multiple choices among the primitive real options. Each compound real options (genes) may assume multiple primitive real options (alleles) and, thus, resulting into a multi-selection problem. Each gene assumes an integer number that corresponds to the index of the module variant associated with the particular primitive real options.

6.3.3 Initialization

Initializing a searching process involves a set of initial solutions which can be developed either randomly or from some heuristic methods (Obitko, 2003). With regards to the feasibility of PFD, an initial population of real options portfolio of size N , $\{x_j^T, x_k^F\}_N$, is determined a priori with the associate of N encoded chromosome strings.

Population size is one of the parameters that is sensitive to the computational performance and the solution quality of the GA, as higher population size allows wider exploration of solution space that results in a better solution. The population size can be derived either via an intensive experimentation (Azadivar *et al.*, 1999) or directly applying the standard values suggested in several existing literature work such as Goldberg (1989), Grefenstette (1986), and Holland, (1975). In this study, a population size of 20 is assigned.

6.3.4 Configuration Constraints Handling

Another important issue is the handling of configuration constraints. In order to obtain feasible solutions, each chromosome must satisfy certain configuration constraints on product configuration from combinations of real options. A number of methods of constraint handling were reported in several literatures, such as the repairing, variable restricting, penalizing, and modifying generic operator methods. In the context of PFD, the rejecting and modifying strategies may be most appropriate (Jiao *et al.*, 2006). At the initialization stage, a rejecting strategy is conducted to handle infeasible chromosomes. Whenever a new chromosome is generated, a configuration constraint check which is described as a set of “IF-THEN” rules is conducted with respect to all types of constraints, and only valid ones are kept in the population and passed on to the offspring. In addition, most existing GA implementations incorporate constraint handling into the GA process.

This makes GA operations very complex and less efficient. In PFD, a separate constraint check module is introduced as a filter that is installed at the outset of the GA process. As a result, only valid chromosomes are involved in the searching space, and thus a standard GA process can be maintained without being intervened by such concerns as the validity of GA operations or the feasibility of each offspring.

Moreover, a modifying genetic operator strategy is proposed to convert the chromosome representation scheme and generate a specialized crossover operator to maintain the feasibility of chromosomes in terms of compatibility constraints. Motivated by the design attribute encapsulation method (Qiu *et al.*, 2002), this research proposes an Options Encapsulation Method (OEM) to modify the genetic operator. Based on the OEM, the overall real options are encapsulated into several groups, such that those real options whose candidates' combinations will result in infeasible

chromosomes are encapsulated in one group. According to the identified interrelationships, incompatible modules are grouped together, for example, real options exercised on modules M_{a1} , M_{a12} , M_{b1} are encapsulated in one group, and real options on modules M_{W3} and M_{RH2} another group. In turn, all combinations of those inter-group real options always produce feasible chromosomes. According to the real options groups, the real options' partitions are mapped into the chromosome representation scheme. Subsequently, crossover can be performed in a particular way – the encapsulated real options within a group will be handled as a whole and the cutting points can occur only at the boundary of groups. As a result, the OEM enables the genetic operator to always generate feasible offspring, thus improving the efficiency of producing feasible chromosomes.

6.3.5 Fitness Evaluation

GA approach adopts a probabilistic search technique based on the principle of natural selection by survival of the fittest and merely uses objective function information, and thus is easily adjustable to different objectives with little algorithmic modification (Holland,1992). Since the primitive objective of PFD is formulated to maximize the expected payoff value, Equation 5-15 can be set as the fitness function for hybrid GA in evaluating and selecting good chromosomes. The fitness function of hybrid GA is a real-valued function, which takes into account both criteria: the technical values of the technical real options subsets and the financial values of the financial real options subsets associated with a chromosome. The former criterion determines the extend of physical flexibility built in a product that satisfies the customer needs, while the latter assesses the management flexibility staged along the project life, which constitutes the justification of profit performance for a product. Since each financial real option treats a technical option as a subproject of PFD

investment, the fitness function is formulated as the multiplication of both the criteria. Eventually, good chromosomes with higher fitness values may expose to higher opportunities to be the parent chromosomes in the succeeding generations whereas poor ones are not to be selected at all.

6.3.6 Selection and Reproduction

According to Darwin's Theory of evolution, the best fitted chromosome survives as parent for creating new offspring. Under the parent selection process, reproductive opportunities are allocated to each chromosome based on its fitness value. The renowned probabilistic selection method namely roulette wheel selection where the roulette wheel is filled with the accumulation of reproduction probabilities assigned to every chromosome. The sizes of the sections on the wheel are proportional to the fitness value of the associated chromosomes, thus, fitter chromosomes will give larger spaces in this biased roulette wheel and accordingly their survival rates are increased.

The advantage of probabilistic selection is that chromosomes with better fitness have higher chances to be kept for the next generation. However, roulette wheel selection may not yield the expected numbers if given the small population. It is also possible that such biased selection may lead to premature convergence when the differences between the fitness values are unreasonably high (Holland, 1992). As the fitter individuals dominate at a much higher proportion of the roulette wheel, the diversity of the population is destroyed, as well as, the performance of the global searching capability of GA. Thus, another probabilistic selection method is attempted in this research which is the rank selection.

Rank selection sorts the population according to fitness values and assigns a count to each chromosome. For example, the worst will be assigned count 1, the second worst count 2, and subsequently, the best will have count K which is the number of

chromosomes in the population. Prior to the selection process, elitism is integrated to duplicate the best chromosome to the mating pool in order to avoid the loss of the best found solution while helping to improve GA performance rapidly (Obitko, 2003).

6.3.7 Crossover

Crossover operator is the main distinguishing step in GA as it imitates the combining of various features of the randomly selected survivors pair, which act as parent chromosomes and form two offsprings. Every offspring, therefore, inherits certain characteristics from both the parent chromosomes. Meanwhile, there are several ways of crossover available that can be determined based on particular fitness function, the encoding schemes and other details of GA (Holland, 1992).

This research adopts a multi-point random crossover operator where parts of the chromosome that contribute to most of the performance of a particular individual may not necessarily be contained in adjacent substrings. Such operator is more robust compared with single-point crossover operator as its disruptive nature encourages the exploration of the search space rather than favoring the convergence to highly fit individuals early in the search.

Solving the PFD issue, a long string chromosome is used to represent the problem which comprises a series of real options that involve the attributes incorporated in a PFD. With single-point crossover, it is unlikely to keep most adjacent substrings intact and this results into premature. In this case, a single-point crossover operator is adopted to encourage the change on each substring. For the whole chromosome, multi-point crossover operation is undertaken. In deciding number of chromosomes of each generation that survives to experience crossover, a crossover rate is given and as practiced here is 0.6. Generally, such rate is chosen based on sensitivity analysis of trial examples using crossover rates ranging between 0.05-0.95.

6.3.8 Mutation

Mutation is the consecutive operation after the crossover where two genes' locations are selected randomly within the offspring to undergo a swap. A small probability is usually assigned for inducing mutation in each generation in order to avoid fast convergence into local optima. Moreover, GA may become a pure random search method if the occurrence of mutation is high. (Holland, 1992) It is suggested the best range of mutation rate is between 0.005 and 0.01 (Obitko, 2003; Gen and Cheng, 2000). As the rule of thumb, a mutation rate of 0.01 is applied to obtain good solutions.

6.3.9 Termination

Various stopping criteria have been addressed in the literature to avoid the possibility of termination issue. The most commonly seen stopping criteria are either when the predefined number of generations is reached or to a circumstance where no variation in the convergence is possible during the rest of generations. By letting the former criterion as stopping rule, the algorithms may over-perform and spontaneously cause an inefficient search as the optimum converges rapidly. While attempting the latter criterion as the stopping rule using the moving average method is suggested as a good indicator for convergence in Balakrishnan *et al.* (1996), if there is a slow convergence. For example, the GA process terminates if the average fitness of the best three strings of the current generation has increased by less than a threshold (namely convergence rate) as compared with the average fitness of the best three strings over three immediate previous generations.

To leverage the above issues, a two-step stopping rule is employed in this research. For the first stopping check, a moving average rule is introduced with the convergence rate of 0.1%. A maximal number of generations given as 1000 is undertaken as the

criterion for the second stopping check. These two rules complement each other. If there is difficulty for the search to converge according to the convergence rate assigned, second stopping rule may activate to avoid infinite run of GA process or vice versa.

6.4 IMPLEMENTATION

The hybrid GA procedure is applied to perform the search among all possible real options portfolio configurations for a maximum expected payoff of PFD. Given a set of diverse customer needs $\{CN_m\}_M$ to be satisfied with the respective optimum PFD, $\{y_k\}_K$ which is achieved according to the optimum real options portfolio generated, $y_k \sim (\{x_r^T\}_R, \{x_s^F\}_S)$ and M modules in each product, y_k . A generic string of the chromosome is defined to be composed of two substrings: technical and financial real options subsets. $(2 * K)$ empty substrings are allocated corresponding to the unselected real options, which contain a total number of $I * M * (2 * K)$ genes with each substring consisting of $\{M_i\}$ genes. Further an allele equal to 0 is introduced as the default value for every gene. This indicates that no corresponding primitive real options is selected to exercise for the PFD configuration.

Subsequently, with I_{jm} possible primitive real options exercised on J_m respective functional features for a module, F_m , an allele that corresponds to the gene may assume from the set, $\{0, 1, 2, \dots, J_m\}_{M_i}$, meaning that a total number of $J_m + 1$ alleles are available for each gene. If all genes throughout a substring assume $\{0\}_{(J+1) \times M}$ alleles, then it means that the corresponding portfolio is not selected in the configuration. In this way, a generic encoding of chromosome enables a unified structure, through which various real options portfolios consisting of different numbers of real options can be encoded within the generic PFD optimization model. Each individual PFD can be

instantiated from the real options portfolio by indirect identification of zero or non-zero alleles for all substrings (Du *et al.*, 2001). Figure 6-6 shows the generic encoding strategy for PFD.

Figure 6-6: Generic encoding for product family design

After encoding, initial solutions to the problem are generated. An initial population of size 20 is determined a priori, therefore, 20 chromosome strings are produced. Moreover, the fitness value of each chromosome string is derived. To evaluate the fitness value of each individual chromosome within the population of each generation, the fitness function is defined as the expected payoff as described in Equation 5-10. At this stage, the rejecting procedure is enacted to screen out those infeasible chromosomes. Through constraint check, only valid chromosomes are passed on for further evaluation. For every generation, the population size is maintained at 20, meaning that only top 20 fit product variants are kept for reproduction.

With respect to the feasible chromosomes, the hybrid GA initiates the reproduction process where the new product configuration alternatives keep being generated through crossover and mutation operations. To leverage possible problems of termination by either convergence or maximal number of generations alone, a two-step stopping rule is

adopted. A moving average rule is used for the first stopping check. The convergence rate is set *ex ante* at 0.7% based on sensitivity analysis of trial examples. Then a maximal number of 1000 generations is specified as the criterion for the second stopping check.

Moreover, in each generation the highest fitness value achieved so far and its corresponding string keep updated and stored. This makes sure that the best product configuration solution found, not only from the final generation but also over all generations, is returned at convergence. Upon termination, the hybrid GA returns the product variants with the highest fitness (expected payoff) as well as the required real options. All intermediate results of each generation (e.g., product variant candidates and their fitness values) and some descriptive statistics (e.g., numbers of crossovers and mutations, average population fitness, population standard deviation and status-quo of product configuration solution) are recorded in the output report. Thus, decision makers can track the progress of the hybrid GA or examine other feasible product configurations that are of high fitness values.

6.5 CASE STUDY

Figure 6-7 shows the moving average errors of the hybrid GA results for the respective customers CNA and CNB that keep being reduced, thus indicating the improvements of fitness values (maximal expected payoffs) along the reproduction process generation by generation. Figure 6-7a shows that certain local optima (e.g., around 5th to 275th generations) are successfully overcome. The saturation period (200-300 generations for customer CNB) is quite short, indicating the hybrid GA search is efficient. In addition, the moving average rule is proven as a reasonable convergence measure which helps avoid such a possible problem that the GA procedure may run unnecessarily up to 1000 generations. For customer CNA, the GA procedure terminates

at the 852th generation which returns an expected payoff of 552.70K. As for customer CNB, a near-optimal design with an expected payoff of 711.63K is achieved at the 299th GA generation.

Figure 6-7: Convergence of the hybrid genetic algorithm solutions

6.6 SENSITIVITY ANALYSIS

Essentially, during the GA searching process, it is important to keep the population diversity. Low diversity may result “inbreeding”, thus weakening the exploratory capability. Many parameters can influence the population diversity. For example, an excessively high crossover rate will cause the solution to converge quickly before the optimum is found. On the other hand, a low crossover rate decreases the population diversity and results in long computation time. The mutation rate also influences the GA performance, as it determines the frequency of random search. Generally, a very low mutation rate is recommended to avoid that the GA process becomes a pure random search, which impairs the property of GA. The population size may be the most distinct factor influencing the population diversity. For a complex problem, large population size is preferred to ensure exploration in a large search space. The performance of the hybrid GA is evaluated by means of sensitivity analysis. Based on

varying parameter values, such as the population size, the crossover and mutation rates, hybrid GA performance is examined for different problem sizes.

6.6.1 Problem Size

In accordance with different parameter values required for varying problem sizes, three cases are constructed to represent three different problem sizes for PFD specification. Table 6-1 lists all three scenarios where simplex case consists of 20 real options (4 technical and 16 financial real options), moderate case consists of 40 real options (8 technical and 32 financial real options), and complex case consists of 85 real options (17 technical and 68 financial real options).

Table 6-1: Problem sizes of three respective scenarios

Problem Type	Problem Size	No. of Real Options	Technical Real Options $\{x_i^T\}_I$	Financial Real Options $\{x_i^F\}_I$
Simple	20	1	$x^{ATTA}(M_{a1new})$	$x^{Lau}(1), x^{Def}(1), x^{Aba}(1), x^{Swi}(1)$
		2	$x^{REMO}(M_{a1})$	$x^{Lau}(2), x^{Def}(2), x^{Aba}(2), x^{Swi}(2)$
		3	$x^{ATTA}(M_{w2new})$	$x^{Lau}(3), x^{Def}(3), x^{Aba}(3), x^{Swi}(3)$
		4	$x^{REMO}(M_{w2})$	$x^{Lau}(4), x^{Def}(4), x^{Aba}(4), x^{Swi}(4)$
Moderate	40	1	$x^{ATTA}(M_{a1new})$	$x^{Lau}(1), x^{Def}(1), x^{Aba}(1), x^{Swi}(1)$
		2	$x^{REMO}(M_{a1})$	$x^{Lau}(2), x^{Def}(2), x^{Aba}(2), x^{Swi}(2)$
		3	$x^{ATTA}(M_{f1new})$	$x^{Lau}(3), x^{Def}(3), x^{Aba}(3), x^{Swi}(3)$
		4	$x^{REMO}(M_{f1})$	$x^{Lau}(4), x^{Def}(4), x^{Aba}(4), x^{Swi}(4)$
		5	$x^{ATTA}(M_{f2new})$	$x^{Lau}(5), x^{Def}(5), x^{Aba}(5), x^{Swi}(5)$
		6	$x^{REMO}(M_{f2})$	$x^{Lau}(6), x^{Def}(6), x^{Aba}(6), x^{Swi}(6)$
		7	$x^{ATTA}(M_{w2new})$	$x^{Lau}(7), x^{Def}(7), x^{Aba}(7), x^{Swi}(7)$
		8	$x^{REMO}(M_{w2})$	$x^{Lau}(8), x^{Def}(8), x^{Aba}(8), x^{Swi}(8)$
Complex	85	Real Options as listed in Table 5-5		

6.6.2 Experiment Design

The proper parameter values for the population size, the crossover and mutation rates are recommended through sensitivity analysis. To setup the experiments, four values are considered for population size, namely 20, 50, 80, and 100. Likewise three

values of crossover rate (0.6, 0.7, and 0.8) and three values of mutation rate (0.005, 0.01, and 0.03) are used. Therefore, sensitivity analysis experiment is constructed based on a $4 \times 3 \times 3$ full design. For more complex analysis, where more values are involved, other experiment design method, such as orthogonal design and factorial design, can be employed. The values of these parameters are selected based on the rule-of-thumb from most of GA applications - a crossover rate at least 0.6 and a very low mutation rate.

6.6.3 Parameter Selection

The full design generates 36 scenarios. For each scenario, the GA runs 10 times to collect the mean value of its performance. Thus, the parameter values for each problem size are recommended on the basis of 360 test runs. The average degree of approximation (Ave_App) associated with GA solutions is adopted as the performance indicator of each problem type. The best GA parameter values are recommended as shown in Table 6-2.

As illustrated in Table 6-2, a larger population size is required for a complex problem in order to keep the population diversity. A population of diverse products is necessary to guarantee thorough exploration in the search space so as to achieve a high degree of average approximation.

Table 6-2: Performance of different problem sizes and respective parameter values

Problem Type	Problem Size	Parameter Value and Performance						Number of Runs
		Population		Crossover		Mutation		
		Size	Ave_App	P _c	Ave_App	P _m	Ave_App	
Simple	20	20	97.3%	0.6	95.6%	0.005	96.2%	360
Moderate	40	50	96.7%	0.7	96.3%	0.01	95.8%	360
Complex	85	100	94.2%	0.8	97.1%	0.03	94.1%	360

The crossover rate (p_c) of 0.8 is recommended to encourage more chromosomes to exchange their promising parts and to generate the offspring with better performance. It also demonstrates the tendency that a higher crossover rate leads to better

approximation. For complex problem, a higher mutation rate is recommended to avoid search's falling into local optimum. For the simple problem type, a lower mutation rate is recommended so that the search becomes a pure random search.

Figure 6-8 shows the average degree of approximation for each population size based on an interval of 20 within the range [20, 160] for the complex problem type. The crossover and mutation rates are set to 0.8 and 0.01, respectively.

Figure 6-8: Performance of different population sizes

As illustrated in Figure 6-8, too large a population size (160) may contribute to the improvement of performance to only a modest extent. Figure 6-9 shows the average degree of approximation for varying crossover rate based on an interval of 0.1 within the range [0.6, 1.0] for the complex problem type. The population size and mutation rate are set to 100 and 0.01, respectively. It suggests that too large a crossover rate may decrease the performance. This is consistent with previous findings from GA applications, that is, a large crossover rate may cause too many chromosomes to change, thus leading to premature.

Figure 6-9: Performance of different crossover rate values

Figure 6-10 shows the average degree of approximation with respect to mutation rate based on an interval of 0.01 within the range of [0.01, 0.05] for complex problem type.

Figure 6-10: Performance of different mutation rate values

The population size and crossover rate are set to 100 and 0.8, respectively. It suggests that too high mutation rates have a negative effect on approximation and seems to disturb the search process by putting too much weight on the random component. For complex problem the recommended mutation rate of 0.03 at the substring level lies within the usual range.

6.7 EFFICIENCY ANALYSIS

The efficiency of a GA lies in generating feasible solutions efficiently and an effective search along the entire generic encoding strategy. In this section, the efficiency of the hybrid GA is examined in terms of the probability of generating feasible solutions and the hybrid GA complexity.

6.7.1 Efficiency Analysis for Feasible Solution Generation

This research adopts the generic encoding strategy to modify the genetic operators. Infeasible chromosomes are encapsulated in one group, and thus combinations of the inter-group real options always produce feasible chromosomes. As a result, the probability of generating feasible solutions is improved, as proven below.

Let $A \equiv \{m_{11}^*, \dots, m_{k2}^*, \dots, m_{K3}^*\}$ be a solution. Suppose all elements of A comprise a set, $E \equiv \{e_1, \dots, e_j, \dots, e_J\}$, where J denotes the total number of elements. Encapsulate all the elements whose combinations result in infeasible solutions in the same group. That is, the set A is divided into G subsets, $S \equiv \{s_1, \dots, s_g, \dots, s_G\}$, where $G \leq K$. Let $N \equiv \{n_1, \dots, n_g, \dots, n_G\}$ be a set of element number of S , where each $n_g \mid \forall g \in [1, 2, \dots, G]$ denotes the number of elements contained in s_g . Then it is true that $J = \sum_{g=1}^G n_g$. Let $W \equiv \{w_1, \dots, w_g, \dots, w_G\}$ and $V \equiv \{v_1, \dots, v_g, \dots, v_G\}$ be two sets of S , where each $w_g \mid \forall g \in [1, 2, \dots, G]$ indicates the number of possible element combinations contained in s_g , and each $v_g \mid \forall g \in [1, 2, \dots, G]$ indicates the number of feasible element combinations. Thus, for each $v_g \mid \forall g \in [1, 2, \dots, G]$, it is true that $v_g \leq w_g$.

The probability of generating feasible solutions without using the OEM is denoted as P_{N_MEM} . It can be calculated as the following,

$$P_{N_MEM} = \sum_{j=1}^J P(fea / e_j) \times P(e_j / wo_c_fea) \times P(wo_c_fea), \quad (6-1a)$$

$$s.t. \quad P(fea / e_j) = \frac{v_1}{w_1} \times \frac{v_2}{w_2} \times \dots \times \frac{v_G}{w_G} = \prod_{g=1}^G (v_g / w_g), \quad (6-1b)$$

$$P(e_j / wo_c_fea) = 1 / \sum_{g=1}^G n_g, \quad (6-1c)$$

$$P(wo_c_fea) = \frac{v_1}{w_1} \times \frac{v_2}{w_2} \times \dots \times \frac{v_G}{w_G} = \prod_{g=1}^G (v_g / w_g), \quad (6-1d)$$

where $P(fea / e_j)$ denotes the conditional probability of generating feasible solutions under the condition that e_j is chosen for mutation; $P(e_j / wo_c_fea)$ indicates the conditional probability of e_j to be chosen for mutation under the condition that the crossover operator generates feasible solutions without following the OEM; and

$P(w_o_c_fea)$ denotes the probability of generating feasible solutions after crossover without applying the OEM.

Combining Equations (6-1a), (6-1b), (6-1c) and (6-1d), P_{N_MEM} is calculated as the following,

$$P_{N_MEM} = \sum_{j=1}^{\sum_{g=1}^G n_g} (e_j / w_o_c_fea) \times \prod_{g=1}^G (v_g / w_g)^2 = \prod_{g=1}^G (v_g / w_g)^2. \quad (6-2)$$

The probability of generating feasible solutions using the OEM is denoted as P_{MEM} , which is calculated as the following,

$$P_{MEM} = \sum_{g=1}^G P(fea / s_g) \times P(s_g / w_c_fea) \times P(w_c_fea), \quad (6-3a)$$

$$s.t. \quad P(fea / s_g) = \frac{v_g}{w_g}, \quad (6-3b)$$

$$P(s_g / w_c_fea) = n_g / \sum_{g=1}^G n_g, \quad (6-3c)$$

$$P(w_c_fea) = 1, \quad (6-3d)$$

where $P(fea / s_g)$ denotes the conditional probability of generating feasible solutions under the condition that s_g is chosen for mutation; $P(s_g / w_c_fea)$ indicates the conditional probability of s_g to be chosen for mutation under the condition that the crossover operator adopts the OEM; and $P(w_c_fea)$ denotes the probability of generating feasible solutions using the OEM for crossover. Abiding by the OEM, the crossover operator always generates feasible solutions, that is, $P(w_c_fea) = 1$.

Combining Equations (6-3a), (6-3b), (6-3c) and (6-3d), the result of P_{MEM} is given as the following,

$$P_{MEM} = \sum_{g=1}^G (v_g n_g / w_g \sum_{g=1}^G n_g). \quad (6-4)$$

Based on Equations (6-2) and (6-4), it can be proven that:

$$\begin{aligned}
P_{MEM} &= \left[(v_1 w_2 \times \dots \times w_G n_1 + v_2 w_1 \times \dots \times w_G n_2 + \dots + v_G w_1 \times \dots \times w_{G-1} n_G) / \prod_{g=1}^G w_g \sum_{g=1}^G n_g \right] \\
&\geq \left[(v_1 \times v_2 \times \dots \times v_G \times n_1 + v_2 v_1 \times \dots \times v_G \times n_2 + \dots + v_G v_1 \times \dots \times v_{G-1} \times n_G) / \prod_{g=1}^G w_g \sum_{g=1}^G n_g \right] \quad (6-5) \\
&= \prod_{g=1}^G (v_g / w_g) \geq \prod_{g=1}^G (v_g / w_g)^2 = P_{N_MEM}
\end{aligned}$$

The result of Equation (6-5) proves that the hybrid GA does improve the probability of generating feasible solutions when adopting OEM.

6.7.2 Complexity Analysis

Although it is always taken for granted that computers are capable of performing any computation, in practice there are a large class of programs that cannot be solved efficiently due to improper construction of the problem itself. Effective data structures thus are of primary importance for reducing complexity of the problem. Based on the generic PFD optimization model, the hybrid GA constructs a configuration space represented by an AND/OR tree structure. The single formalism enables the efficient and effective search patterns, thus decreasing the difficulties in solving the PFD problem.

With a generic PFD optimization model, the configuration space can be assumed to be represented as a balanced tree. Let H be the height of the tree, and n be the node number at every level of the tree. Then the total number of nodes is given as n^{H-1} . This requires $O(n^H)$ comparisons for each solution to be found. When this process continues to rank all the solutions, the complexity becomes $O(n^H)$.

Given a total number of n^{H-1} variables, a regular GA, where no generic structure is available to describe the variables, requires $O(n^{H^H})$ comparisons for each solution to

be found. When this process continues to rank all the solutions, the complexity becomes $O(n^{H^H})$. Such a comparison of complexity clearly suggests that the PFD data structure based on the generic PFD optimization model reduces the complexity of the GA search substantially. Therefore, the hybrid GA is much advantageous over any regular GA approach.

6.8 SUMMARY

Product family design inherently encounters a combinatorial explosion problem, which is known to be mathematically intractable or NP-hard. Although GA excels at solving combinatorial optimization problems, either a specific or universally applicable GA has difficulties in dealing with the PFD problem, where diverse PFD scenarios and complex constraints always exist. The hybrid genetic algorithm aims to improve the effectiveness and efficiency of GA-based PFD.

Generic encoding enables hybrid GA to adapt to diverse PFD scenarios without encoding the entire solutions within a single chromosome. A hybrid constraint-handling strategy helps handle complex and distinct constraints at different stages of the evolutionary process. Efficiency analysis indicates that the hybrid genetic algorithm improves the probability of generating feasible solutions. Complexity analysis also proves that the hybrid genetic algorithm outperforms regular genetic algorithms for product family design.

CHAPTER 7:

PRODUCT PLATFORM FLEXIBILITY PLANNING

The rationale of a product platform has been well recognized as one of the effective technologies to achieve mass customization. In practice, a product platform performs as a base product, from which product families can variegate designs to satisfy individual customer requirements. Investing such product technology (product platforms) creates flexibility for the company to accommodate future customization requirements while taking a risk by increasing complexity in design and production. Having several technology options to satisfy various markets, a decision maker usually faces difficulty in stating a priori planning of product platform so as to maximize the potential payoff of the large irreversible investment in technologies. This chapter discusses the economic justification on the flexibility of product platforms.

7.1 CHARACTERIZATION OF FLEXIBILITY AND UNCERTAINTY

Let $\Pi = \{PdP_j | j = 1, \dots, J\}$ and $\mathbf{M} = \{M_s | s = 1, \dots, S\}$ be the non-dominated sets for the product platform options and markets, respectively. As a rule of thumb, flexibility is not free and thereby, the flexibility of product platforms can be characterized in two ways: (1) it is able to serve more than one customer demand from various markets, or (2) it is dedicated only to fulfill customer demands in a specific market.

According to de Groote (1994)'s notation for flexibility, product platform PdP_1 that is more flexible than product platform PdP_2 , is noted as $F(PdP_1) \geq F(PdP_2)$, where

$F(PdP_j)$ denotes the flexibility of product platform PdP_j in terms of utility. By holding the market demand fixed, product platform PdP_1 with a higher flexibility and a lower cost than product platform PdP_2 , is said to dominate product platform PdP_2 , which can be expressed as follows:

$$C(PdP_1) \geq C(PdP_2) \Leftrightarrow F(PdP_1) \geq F(PdP_2), \quad \forall PdP_j, \quad (7-1)$$

where PdP_2 will never be the optimal product platform, in which it can be deleted from the set Π without affecting the solution to the problem. As a note, the relationship may differ with respect to different markets.

While referring to the general gist of flexibility, a certain level of flexibility is only valuable if the uncertainty of a future customer demand is successfully cushioned by a given premium that enables to overcome the associated investment costs. Higher return is expected if a higher uncertainty is dissolved according to the options concept. In that case, if the demand in market M_1 is more diverse than that in market M_2 , it is noted as $U(M_1) \geq U(M_2)$, where $U(M_s)$ denotes the uncertainty of the demand in market M_s . This implies that the potential payoff (PP) from market M_1 , $PP(M_1)$ is greater than that from market M_2 , $PP(M_2)$, such that:

$$PP(M_1) \geq PP(M_2) \Leftrightarrow U(M_1) \geq U(M_2). \quad (7-2)$$

As for the relationship between flexibility and potential payoff, it can be determined by assuming the initial investment costs for all product platforms to be equal. For any market M_s , if product platform PdP_1 performs more flexibly than product platform PdP_2 , the PP for product platform PdP_1 is said to be explicitly greater than the PP for product platform PdP_2 , such that:

$$F(PdP_1) \geq F(PdP_2) \Leftrightarrow PP(M_s, PdP_1) \geq PP(M_s, PdP_2). \quad (7-3)$$

7.2 TRADEOFFS AMONG FLEXIBILITY, UNCERTAINTY, AND POTENTIAL PAYOFF

Making decisions about flexibility often involves tradeoffs among the marketing, design, and production departments; however, all these aspects are seldom tackled by the existing approaches within a coherent and integrated framework (Tseng and Jiao, 2001). Given the multidimensional nature of product platforms in configure-to-order production, it rises in importance to achieve a synergy among uncertain market/customer demands, costs and potential payoff of product platform throughout the design customization. Illustrations of the tradeoffs scenarios among the uncertainty, flexibility level, and expected potential payoff are provided in Figure 7-1.

Flexibility is assumed to be free in the scenario, as shown in Figure 7-1(a). If there is no uncertainty involved in the customization, the potential payoff of the product platform investment may remain constant even the increase of flexibility level. On the other hand, if the uncertainty is low, any increase in the flexibility level may result in a higher potential payoff of product platform investment. Relatively, as uncertainty becomes more prevalent, an even greater potential payoff at each flexibility level is expected.

Figure 7-1(b) shows a scenario, whereby the cost charged at each level of flexibility is relatively low compared to the corresponding potential payoff. In addition, the costs vary in terms of different situation types. For example, a more flexible product platform may be more expensive to invest or less efficient to implement than a less flexible product platform due to the higher cost involved. Meanwhile, if there is no involvement of uncertainty, a product platform with the positive cost of flexibility may experience a

decline in the potential payoff as the level of flexibility increases. In contrast, the flexibility of product platform becomes valuable at each level under the low uncertainty degree. It is due to the low flexibility cost relative to the corresponding potential payoff. Intrinsically, it is even worthwhile to execute the product platform options for each level of flexibility as the uncertainty increases.

Figure 7-1: Tradeoffs between the potential payoffs and the levels of flexibility

Figure 7-1(c) shows a scenario where the flexibility is not valuable when the uncertainty degree is low as the potential payoff of flexibility is low relative to its cost. Namely, it is too costly to implement an exaggerated level of flexibility when a low degree of uncertainty exists. Despite that, in certain circumstances, a particular degree of uncertainty is deserved to be resolved at a certain level of flexibility.

The last scenario, as shown in Figure 7-1(d) occurs when the flexibility is relatively more expensive than the corresponding potential payoff. Regardless of the uncertainty, a higher level of flexibility eventually implies a lower potential payoff. This further explains that even the uncertainty is successfully cushioned by certain level of flexibility; it does not necessary valuable to a company due to the corresponding potential payoff fails to compensate the substantial incurred costs.

7.3 FLEXIBILITY PLANNING BASED ON REAL OPTIONS

Corresponding to multiple customer demands (a set of customization requirements) across diverse market niches, there are several strategic options by which product platforms can influence the current- and future- customization requirements. Therefore, flexibility planning is crucial to assist companies in determining an appropriate level of product platform flexibility in product family design and platform-based product development.

Flexibility planning of a product platform extends the flexibility analysis of the proposed hybrid real options valuation for PFD. Modeling such problem is rather complex as it involves several PFD problems which are configured on various product platforms that are developed based on different sets of design parameters, $\{DP_m | m = 1, \dots, M\}$ to meet certain customer demand characterized by a set of functional features, $\{F_j | j = 1, \dots, J\}$.

7.3.1 Uncertainty

As mentioned in Chapter 3, customer demand uncertainty is reckoned as the key factor faced by a firm during the configuration for an optimal PFD. Likewise, it is applicable to the problem of product platform flexibility planning.

A customer-perceived utility is realized as an appropriate uncertain parameter to model such uncertainty. Du *et al.* (2003) study the formulation of utility function for quantifying the customer-perceived value of design customization. It begins with an experiment design of ranges and levels for each customization requirement; test profiles are constructed and presented to the respondents to access customer preferences according to appropriate scales of utility. Subsequently, the customer's subjective preference for customization is quantified as the utility with respect to the overall performance of product features. Based on such a quantitative measure, standard statistical analysis techniques are used to estimate the utility function. For example, the part-worth and configural models are popularly-used preference models.

As multiple features, i.e., $\Delta F \sim \{\Delta F_i \mid i=1, \dots, n\}$, are usually involved in a customer demand, the customer-perceived utility with respect to a customer demand has therefore been modeled as a joint utility function of individual utilities for every configurable feature, as shown in Equation (7-4).

$$PU(\Delta F) = \sum_{i=1}^n (w_i U_i(\Delta F_i)), \quad (7-4)$$

where w_i indicates the relative importance (customer preference) of each feature. $U_i(\Delta F_i)$ denotes the part-worth utility of each individual feature.

Conjoint analysis is an effective approach used to measure the customer preference and assess utility functions for multiple product attributes (Green and DeSarbo, 1978). Considering that a large number of attributes may be involved in a customer demand, this research applies adaptive conjoint analysis (Sawtooth Software, 2002) to explore customer utilities by asking customers to rate a group of testing profiles in an interactive setting. Response surfaces are created to simulate testing profiles. Other

approaches, such as Kano Diagrams (Kano *et al.*, 1984) and the Analytic Hierarchy Process (Saaty, 1980) can also be applied to refine utility values.

Since customer demand is diverse across various market niches, $\{M_s | s = 1, \dots, S\}$, Equation (7-5) is formulated to characterize the customer demands in terms of customer-perceived utility that evolve according to GBM.

$$dPU_i^{M_s} = \mu PU_i^{M_s} dt + \sigma PU_i^{M_s} dZ. \quad (7-5)$$

To resolve such heterogeneous uncertainties, vigilant selections are required on the available product platforms; otherwise, the outcomes may influence the customer satisfaction of the PFD offering. In this regard, a frequent revision of the product platforms' flexibility is necessary via flexibility planning, so as to ensure the customer demands are well-fulfilled and the company's potential payoffs are not distorted.

7.3.2 Assumptions

Several assumptions are made in the formulation of product platform flexibility planning, as listed in the following:

- Market M_s is characterized by the customer demand at time period t , $CN_i^{M_s}$, which can be quantified as a stochastic variable. For each market $M_s \in \mathbf{M}$, there exists a known demand distribution $GBM^{M_s}(PU_{it})$. In addition, initial customer demands are known (i.e., at $t = 0$);
- The uncertain parameter is described in terms of the customer-perceived utility derived by conjoint analysis;
- Process platforms are constructed corresponding to the product platforms; therefore, the configuration of process platform is not taken into consideration;
- Under the flexibility planning, decision maker must make a choice among the current available product platforms, so as to maximize the potential payoff of a

- given market-product platform pair, (M, PdP) , with respect to the customer satisfaction; and
- In a system with full customization flexibility, the switch between product platform options can be achieved very quickly with very low cost, i.e., $C(PdP_{i \rightarrow j}) = \varepsilon, \forall PdP \in \Pi$, where ε is a very small number.

7.3.3 Formulation

To select the most appropriate alternative from a finite set of market-product platform pairs, the potential payoff, $PP(M, PdP)$, is meant to be the primary measurement among other valuation criteria, which assesses the cost effectiveness of flexibility of a particular product platform. As the ultimate goal of the product platform flexibility planning is to determine an optimal pair of the flexible product platform and the uncertain market, (M^*, PdP^*) , the objective function is then defined as the maximization of the potential payoff of the market-product platform pair, i.e., $PP(M^*, PdP^*) = \max_{\mathbf{M}, \Pi} PP(M, PdP)$.

Considering a firm has invested in a set of product platforms, $\Pi = \{PdP_j | j = 1, \dots, J\}$, which is embedded in various product platforms to fulfill the heterogeneous customer demands, $\mathbf{Y}_{M \in \mathbf{M}} = \{PU_i^{M_s} | i = 1, \dots, n\}$, at every period of time, $\mathbf{T} = \{t | 0, \dots, T\}$. As reviewed in Jiao and Tseng (1998), product platform flexibility analysis exhibits the classic multi-criteria alternative valuation problem. For each product platform, a deterministic flexibility plan can be formulated for every time period along each propagation path of uncertain parameters. Accordingly, a mathematical program is formulated to determine the expected potential payoff for all market-product platform pairs, $(M, PdP) \in \mathbf{M} \times \Pi$, such that:

$$E[PP(M, PdP)] = \max \sum_{s=1}^S \sum_{i=1}^I \sum_{t=1}^T E[V(y_{sit})] \quad (7-6a)$$

$$\text{s.t.} \quad V^T(X_{iPdP_j}^T) V^F(X_{iPdP_j}^F) = E[V(y_{iPdP_j})] \quad \forall (i \in \mathbf{Y}, PdP_j \in \mathbf{\Pi}) \quad (7-6b)$$

$$E[V(y_{sio})] = E^*[V(y_{iPdP_j 0})] \quad \forall (i \in \mathbf{Y}, PdP_j \in \mathbf{\Pi}) \quad (7-6c)$$

$$V^T(X_{iPdP_j}^T) V^F(X_{iPdP_j}^F) > 0 \quad \forall (i \in \mathbf{Y}, PdP_j \in \mathbf{\Pi}) \quad (7-6d)$$

Equation (7-6a) is the objective function to maximize the expected potential payoff over the planning time horizon. Equation (7-6b) presents the expected potential payoff of PFD y_{iPdP_j} , as defined in Equation (5-15), which describes the relationships between the payoff value and cost of PFD on a product platform PdP_j at a flexibility level $F(PdP_j)$. Equation (7-6c) prescribes the payoff value of PFD y_{sio} at the beginning of planning time horizon. Equation (7-6d) ensures that the payoff value and cost variables return the positive values.

Flexibility planning involves decision-making under uncertain circumstance, where several strategic decisions such as switch, upgrade, abandon, and launch options take place. All the strategic decisions identified are assumed to be European options. Under such an assumption, a decision maker is allowed to make the best possible set of strategic decisions at any point of time, given current available information. However, not all of these decisions have to be implemented immediately. A decision is subject to revision; usually a decision is not implemented until the last possible moment. The descriptions and formulations for those strategic decisions involved in the product platform flexibility planning are given as follows:

(1) *Switch option*. This option is exercised when the product platform PdP_j is performed better than the product platform PdP_i with respect to their potential payoff, which is formulated as follows.

$$x^{Swi}(PdP_{i \rightarrow j}, t) = \max(E[PP(M_s, PdP_j)] - C(PdP_{i \rightarrow j}), E[PP(M_s, PdP_i)]), \quad (7-7)$$

$$\forall (M_s \in \mathbf{M}, PdP_j \in \mathbf{\Pi}, t \in \mathbf{T}),$$

where $C(PdP_{i \rightarrow j})$ is the cost incurred by switching between product platform alternatives.

(2) *Upgrade option.* Upgrading of the current product platforms (product technologies) is necessary if the performances are unfavorable, corresponding to the customer demands across diverse market niches at time period t . To exercise this option, the following equation is to be satisfied.

$$x^{Upg}(PdP_j, t) = \max(e_t * E[PP(M_s, PdP_j)] - I_t, 0), \quad (7-8)$$

$$\forall (M_s \in \mathbf{M}, PdP_j \in \mathbf{\Pi}, t \in \mathbf{T}),$$

where e_t and I_t denote the increased rate of potential payoff and the investment outlay of new product platform at time period t , respectively.

(3) *Abandon option.* As the performances of product platforms decline severely, a firm may consider abandoning the current product platforms, meanwhile, realizing the salvage value of the current product platforms. The payoff value of the abandon option can be determined from the following equation:

$$x^{Aba}(PdP_j, t) = \max(S_t, E[PP_t(M_s, PdP_j)]), \quad \forall (M_s \in \mathbf{M}, PdP_j \in \mathbf{\Pi}, t \in \mathbf{T}), \quad (7-9)$$

where S_t denotes the salvage value of PdP_j at time period t .

(4) *Launch option.* Launch option is undertaken when the current product platforms are still performing the best in satisfying the customer demand, and their potential payoffs are given as follows:

$$x^{Lau}(PdP_j, t) = \max(E[PP_t(M_s, PdP_j)], x^{Upg}, x^{Aba}), \quad \forall (M_s \in \mathbf{M}, PdP_j \in \mathbf{\Pi}, t \in \mathbf{T}) \quad (7-10)$$

7.3.4 Pricing Model

Flexibility planning of product platforms is viewed as a long term planning, which involves the exercise of a series of identified options (i.e., switch, abandon, upgrade and launch options) along an expected planning time horizon, T , of three to five years (Katok, 1996). This eventually creates a nested new option that is analogous to a compound option.

The potential payoff of a compound option, ψ , throughout each planning path can be determined by the summation of individual current period payoff for all periods, which must satisfy the following partial differential equation based on the options theory (Trigeorgis, 1996):

$$\frac{\partial \psi(T)}{\partial t} + \sum_{i=1}^n (r - \delta_i) PU(CN_i) \frac{\partial \psi(T)}{\partial PU(CN_i)} + \frac{1}{2} \sum_{i=1}^n \sum_{k=1}^n PU(CN_i) PU(CN_k) \frac{\partial^2 \psi(T)}{\partial PU(CN_i) \partial PU(CN_k)} - r\psi(T) = 0, \quad (7-11)$$

where r is a risk-free rate.

Solving the above partial differential equation analytically is rather tedious and almost impossible due to the complex terminal boundary conditions. Therefore, a multivariate binomial lattice approach is integrated to project the expected potential payoff, $PP(M, PdP)$, along the timeline by adding up all the potential payoff values of real options for every path, and subsequently multiplying with the corresponding probabilities of uncertain parameters. Finally, based on a comparison of the potential payoffs for all possible paths, the optimal portfolio of M^* and PdP^* can be generated.

The involvement of multiple product platforms in multiple PFD configurations to fulfill multiple customer demands across diverse market niches, has made the flexibility planning problem more complex and NP-hard in finding the best environment-technology pair, (M^*, PdP^*) .

Alternatively, a decision maker may prefer a market-product platform pair that yields the most attractive combination of uncertainty and potential payoff. Table 7-1 gives an algorithm pertaining to the solving of the above problem. In practice, the variables and parameters may be different with respect to different market-product platform pairs.

Table 7-1: Algorithm for solving the flexibility planning model based on real options

$PP(M, PdP) = 0;$
foreach $((M, PdP) \in \mathbf{M} \times \Pi)$ do
Construct a multivariate lattice based on problem parameters;
Foreach (every path in the lattice) do
$E[V(y_{sio})] = E^*[V(y_{iPdP,0})];$
foreach $t \in (1, \dots, T)$ do
Solve the mathematical program (Equation (7a)-(7d)) for $(M, PdP);$
$E[V(y_{sio})] = E[V(y_{sit})];$
$E[PP(M, PdP)] = \max \sum_{s=1}^S \sum_{i=1}^I \sum_{t=1}^T E[V(y_{sit})];$
$PP(M, PdP) = PP(M, PdP) + Pe^{-rt} E[PP(M, PdP)];$
endfor ;
endfor ;
endfor ;
$PP(M^*, PdP^*) = \max_{(M, PdP) \in \mathbf{M} \times \Pi} PP(M, PdP);$

7.4 CASE STUDY

7.4.1 Background

A case study on vibration motor design customization is performed to validate the proposed product platform flexibility planning model. The PFD strategies differentiate

in the fulfillment of diverse customer needs using different product platforms. The needs of two customers, CNA and CNB, are defined in this study and the specifications of respective customer needs are given in Table 7-2. In this case, three product platforms (product technologies): PdP₁, PdP₂, and PdP₃, are selected, and given the specifications are listed in Table 7-3. Hence, there are totally $(2 \times 3) \times 6 = 36$ pairs of market-product platform to be analyzed.

Table 7-2: Specifications of customer needs for CNA and CNB

Functional Feature $\{CN_m\}_M$		Individual Customer Needs $[CN_m^L, CN_m^U] \ \& \ u(CN_m)$	
		Customer CNA	Customer CNB
Armature (A)	A1(Current / mA)	60±15 / Triangular	80±20 / Triangular
	A2(Pb free)	N / Uniform	Y / Uniform
Frame (F)	F1(Length / mm)	9.5±3 / Triangular	13.5±4 / Triangular
	F2(Diameter / mm)	10±4.5 / Triangular	19±8 / Triangular
Bracket (B)	B1(Color)	R / Uniform	B / Uniform
	B2(Connected Method)	U / Uniform	M / Uniform
	B3(Coating)	N / Uniform	Y / Uniform
Weight (W)	W1(Shape)	P / Uniform	U / Uniform
	W2(Holding Strength / kg)	4±2.5 / Triangular	5±3 / Triangular
	W3(Speed / rpm)	5500±200 / Triangular	10500±1500 / Triangular
Magnet (M)	M1(Pb free)	N / Uniform	Y / Uniform
Rubber Holder (RH)	RH1(Color)	R / Uniform	B / Uniform
	RH2(Shape)	P / Uniform	T / Uniform

Since the market environment is relevant to the financial performance of product platform and is perfectly correlated with customer demand, six uncertain market scenarios in terms of product demand are considered in this study.

The uncertain market scenarios range from an almost deterministic market M1 with the lowest demand volatility to an extremely variable market M6 with the highest demand volatility. Volatility appears to be a reasonable measure of demand uncertainty regarding variety. Figure 7-2 illustrates the tendencies of the six market scenarios' demands that deviate according to the volatility parameters, as given in Table 7-4.

Table 7-3: Specifications of product platforms

Functional Feature $\{CN_m\}_M$	Product Platform (Customer Needs per Market Segment) $[F_{iq}^L, F_{iq}^U] \& u(F_{iq})$		
	PdP ₁	PdP ₂	PdP ₃
A1	[50, 70] / Triangular	[65,80] / Triangular	[85, 110] / Triangular
A2	[Y, N] / Uniform	[Y,N] / Uniform	[Y, N] / Uniform
F1	[8.5, 12] / Triangular	[11,15] / Triangular	[14, 17] / Triangular
F2	[6.5, 15] / Triangular	[11,19] / Triangular	[15, 27] / Triangular
B1	[R, W, B] / Uniform	[R, Y, B] / Uniform	[R, B, G] / Uniform
B2	[U, X, L] / Uniform	[U, F, D] / Uniform	[U, M, T] / Uniform
B3	[Y, N] / Uniform	[Y, N] / Uniform	[Y, N] / Uniform
W1	[P, T] / Uniform	[P, T, U] / Uniform	[P, T, U] / Uniform
W2	[2.5, 5] / Triangular	[3.5, 6.5] / Triangular	[5.5, 8.5] / Triangular
W3	[5000, 9200] / Triangular	[8000, 10000] / Triangular	[9500, 14000] / Triangular
M1	[Y, N] / Uniform	[Y, N] / Uniform	[Y, N] / Uniform
RH1	[R, W, B] / Uniform	[R, Y, B] / Uniform	[R, B, G] / Uniform
RH2	[P, T] / Uniform	[P, T, U] / Uniform	[P, T, U] / Uniform

Figure 7-2: Demand tendencies of all respective markets

Other parameters describing the market environments include the initial product demand, the increase rate, the risk-free rate, the risk premium, and the available capacity. All the data are presented in Table 7-4, which are determined based on the best currently available forecast of their averages.

Table 7-4: Uncertainty of market demand

Market $\{M_s\}_S$	Product Demand Distribution			Others
	Increase Rate	Volatility, $U(M_s)$	Initial Demand	
M1	0.5%	0.0	10000	Risk-Free Rate = 0.05 Risk Premium = 0.0 Capacity = 20K
M2	1%	0.2	11000	
M3	5%	0.4	11500	
M4	10%	0.5	12000	
M5	15%	0.7	12500	
M6	20%	0.9	13000	

7.4.2 Analysis

(1) *For Customer CNA.* With respect to various market uncertainties, the results of the potential payoff for customer CNA with the underlying product platforms are shown in Figure 7-3. Apparently, two phenomena have found under the conditions when the market volatility rates are <0.5 and ≥ 0.5 respectively.

When the market volatility rate is less than 0.5, markets M1, M2, and M3 are satisfied with the relatively low costs compared to the corresponding potential payoff for each product platform (i.e. PdP_1 , PdP_2 , and PdP_3). As the cost of flexibility varies with respect to market uncertainty, the product platform, PdP_3 , seems to be more expensive to invest and less efficient in dealing with the market scenario M1. As a result, there is a decline in the potential payoff of product platform PdP_3 , compared to the product platform PdP_2 .

In addition, both product platforms, PdP_2 and PdP_3 are feasible to be executed or shared within the market scenarios M2 and M3, given their relatively high potential payoffs. However, as the market volatility rate reaches 0.5 or even greater, the phenomenon observed is similar to the scenario shown in Figure 7-1(c). Obviously, the product platform PdP_2 is the most profitable to employ in handling the market scenarios

M4 and M5. As for market scenario M6, it is worthwhile to invest in the product platform PdP_3 , although the yielded potential payoff is not as substantial as that in other market scenarios.

Figure 7-3: Performance of different market-product platform pairs for customer CNA

(2) *For Customer CNB.* In terms of the potential payoff, Figure 7-4 presents the financial performances of six product platforms under different market scenarios.

Figure 7-4 demonstrates that the cost of each product platform varying in the degree of flexibility is low relative to the potential payoffs.

Despite the costs incurred at each flexibility level are positively low, it deviates with respect to the degrees of uncertainty associated with different market scenarios. In this case, with the increase in the market scenario's uncertainty, the product platform PdP_3 is reckoned to outperform those low-and medium-end product platforms. Moreover, as customer CNB belongs to the high-end market per se, the PFD based on the high-end product platform, i.e. PdP_3 , has, therefore, provided the highest potential payoff among all the product platform investments.

Figure 7-4: Performance of different market-technology pairs for customer CNB

7.4.3 Results

The overall potential payoffs of the market-technology pairs involved in the product family designs for customers CNA and CNB are summarized in Table 7-5.

Table 7-5: Overall potential payoff of the market-product platform pairs involved

Market Scenario	CNA			CNB		
	PdP ₁	PdP ₂	PdP ₃	PdP ₁	PdP ₂	PdP ₃
M1	10K	62.227K	35.862K	5K	10K	11.62K
M2	11K	71.131K	62.635K	5.5K	11K	12.782K
M3	11.5K	41.515K	66.621K	5.75K	11.5K	13.783K
M4	12K	89.302K	15.273K	6K	12K	14.112K
M5	12.5K	77.784K	46.875K	6.25K	12.5K	13.94K
M6	13K	21.333K	28.080K	6.5K	13K	15.581K

A better visualization is given in Figure 7-5 showing the flexibility performances of the six product platforms, as well as, the evidence of the presence of product platforms

which influences the financial performance of PFD variously with respect to the market uncertainty. Accordingly, the flexibility planning of product platforms is accomplished.

Figure 7-5: Overall performances of product platforms for different product family designs

The figure shows that the flexibility of the low-end product platform, i.e. PdP₁, contributes the least potential payoff in customizing designs (CNA@PdP₁ and CNB@PdP₁) as compared to other product platforms, i.e., PdP₂ and PdP₃. In this regard, the abandon and upgrade options are recommended to be exercised on this low-end product platform investment.

Meanwhile, for the more flexible product platforms, i.e. PdP₂ and PdP₃, the increasing trend in the potential payoffs is demonstrated compared to the product platform PdP₁. While customizing design solutions for customer CNA based on the medium-end product platform (CNA@PdP₂), its flexibility seems to become more profitable than the high-end product platform PdP₃ when the market uncertainty increases. In addition, a local maximum is suggested at CNA@PdP₃ and M2. This has coincided with the practical concerns – always seeking for a market with the best potential payoff (characterized by M2) while maintaining the most cost-effective PFD

capability (indicated by CNA@PdP₂). However, when the market uncertainty reaches the maximal as M6, the high flexible product platform, PdP₃, is suggested to maintain the most cost-effective PFD capability.

The increasing uncertainty in the market results in a diminishing benefit from using less flexible product platforms. In this case, switch options can be adopted between product platforms PdP₂ and PdP₃ for market scenarios M3 and M4, as shown in Figure 7-6, given the value of less than or equal to 25.106K and 6.747K respectively. Subsequently, it limits the over-capacity issues during the configuration.

Figure 7-6: Value of flexibility planning based on real options for customer CNA

However, the flexibilities of the three product platforms, involved in the PFD for customer CNB (CNB@PdP₁, CNB@PdP₂, and CNB@PdP₃) show no prominent profitability among the six market scenarios. In general, the high-end product platform PdP₃, possessing the highest degree of flexibility, manages to provide the highest potential payoff, meanwhile accommodating the need of customer CNB from less to high uncertain markets. The cost incurred in the PFD becomes less critical, that is the low variable cost, when the market uncertainty is high. This indicates that it is valuable to invest in the product platform.

7.5 SUMMARY

Investing into product platforms creates options for the company to accommodate future mass customization requirements. The company possesses the flexibility to make choices, over the course of developing product families, such as developing product family design based on existing platforms, developing the desired products individually, configuring the desired products based on many options of platform elements, and so on. Flexibility of these real options bestows extra values to the firm by hedging against volatility and

turbulence in the market, design, and production. Realizing the value of flexibility inherent in a product platform, it has led to significant improvements for product family design in terms of economic value. These improvements are more promising when the uncertain demands are considered and the downstream costs are relatively large. This chapter demonstrates the product platform flexibility planning model for PFD using real options. The model is developed to avoid unfavorable circumstances and to take the advantage of favorable opportunities. The valuation of real options sheds light on the tradeoffs among the uncertainty, the flexibility, and potential payoff during product family design configurations.

CHAPTER 8:

CONCLUSIONS AND FUTURE WORK

This chapter concludes overall findings of this research with respect to the research objectives and scopes. Contributions of the research in terms of deliverables and theoretical relevance are revisited. Finally, the limitations and future directions of this research are outlined based on the status quo.

8.1 CONCLUSIONS OF THIS DISSERTATION

Recognizing the importance of PFD economic justification in mass customization, this dissertation is aimed to study the valuation of PFD from both the technical and financial perspectives. In correspondence to the identified objectives and scopes, the achievements and findings are concluded as follows.

8.1.1 Real Options Framework for Product Family Design

Substantial progress had been witnessed towards PFD optimization, product family modeling, product family decision support, and so on. To avoid an illusive repackaging of existing ideas and misconceptions with only limited synthesis, the basic rationale of PFD thoroughly within a coherent framework has been investigated. The general gist of platform-based product development originated from its economic justification considering uncertainty and flexibility.

In this regard, a real options approach has been introduced, as the strategy for solution owing to its strength in taking into account of the flexibility, uncertainty, and

irreversibility. The real options framework formulated for PFD, clearly recognizes the value of flexibility management and models the exercise of choices at key decision points along the PFD project life. Along this process, a consistent choice of the risk-free discount rate is permitted for the valuation due to the constantly diversified project risks and realized market risks in the options analysis. The case study indicates that real options models deserve a place in toolkits of decision-making for the uncertain and irreversible PFD investment.

8.1.2 Hybrid Real Options for Product Family Design Optimization

As far as a PFD project is concerned, the value of flexibility improves, as do options, when there is more risk. This is because the ability to avoid unfavorable circumstances or to take advantage of favorable opportunities is more valuable when there are greater prospects of exploiting flexibility inherent in product platforms. To determine the value of flexibility both inherent in a PFD project and built in the product platform, hybrid real options has been identified, comprising product-related and project-related options, to integrate engineering and financial analyses into a coherent framework. It utilizes the knowledge of the technical and financial experts for the respective evaluation of product and project related flexibility.

The hybrid valuation model has been formulated as multivariate partial differential equations, which are difficult to achieve analytical solutions due to the fact that terminal boundary conditions are very complex. Toward this end, this research has developed a numerical options pricing method, called MLTBL for the PFD valuation, where the jump sizes are defined as a priori in order to choose the jump probabilities to match the characteristic functions. The rationale of the MLTBL approach coincides with Trigeorgis's (1991) LTBL by extending the one-asset case to the n -assets case. Comparative studies of the MLTBL approach with other lattice approaches suggest that

MLTBL approach ameliorates other approaches in terms of consistency, stability and efficiency. Furthermore, the MLTBL approach can achieve similar performance as other approaches while alleviating their deficiency in maintaining reasonable up- and down-jump sizes.

Hybrid PFD optimization inherently encounters a combinatorial explosion problem. Although GA in general excels in solving combinatorial optimization problems, either a specific or universally applicable GA has difficulties in dealing with the PFD problem, where diverse PFD scenarios and complex constraints always exist. The hybrid GA is developed to improve the effectiveness and efficiency of searching for an optimum of PFD. The hybrid GA has demonstrated some unique features: (1) Generic encoding enables hybrid GA to adapt to diverse PFD scenarios without encoding the entire solutions within a single chromosome; and (2) A hybrid constraint-handling strategy helps handle complex and distinct constraints at different stages of the evolutionary process. The performance of the GA is verified through sensitivity and efficiency analyses.

An application of the hybrid real options framework to a vibration motor manufacturer illustrates the feasibility and potential of the proposed approach. As witnessed in the case study, the implementation of this method is straightforward. Most importantly, this approach leads to significant improvements in the value of PFD. These improvements are more promising when uncertain demands are concerned, and when the downstream costs are relatively large.

8.1.3 Flexibility Planning of Product Platforms

Investing into product platforms creates options for the company to accommodate future mass customization requirements. The company possesses the flexibility to choose, over the course of developing product families, whether to develop variants

based on existing platforms or develop the desired products individually, or to configure the desired products based on many options of platform elements. Flexibility of these real options bestows extra values to the company by hedging against volatility and turbulence in the market, design and production.

Realizing the value of flexibility inherent in a product platform can lead to significant improvements for PFD in terms of economic value, in particular, when considering uncertain demands and downstream costs. This research has developed a product platform flexibility planning model in accordance with the real options framework to avoid unfavorable circumstances and to take advantage of favorable opportunities. The valuation of real options sheds light on the tradeoffs among the uncertainty, the flexibility, and potential payoffs from product family design configurations.

8.2 CONTRIBUTIONS

This research has bestowed several contributions for the product family design and platform-based product development. The major contribution of this research is the development of hybrid real options valuation framework. The deliverables can be summarized from the strategy, fundamental, methodology, tool, application, and verification aspects.

(1) At the strategic level, the following observations are derived:

- The inadequacy of traditional capital budgeting in justifying the PFD economically is realized through identifying underlying issues of economic value, uncertainty, and flexibility.

(2) As for the fundamentals, the following achievements are reached:

- A comprehensive review on the background and state-of-art PFD and platform-based product development research provides an in-depth critique of the existing valuation frameworks; and

- A synthesis of the options theory and PFD in terms of the understanding of valuation properties involved in product families and platforms, including the time period until investment opportunity disappears, uncertainty of expected cash flows, present value of expected cash flows, value lost over duration of option, risk-free interest rate, and present value of fixed costs.

(3) At the methodology level, the deliverables can be summarized as follows:

- The application of a real options theoretic approach to overcome those overlooked issues in the traditional economic valuation approaches by identifying real options associated with PFD and considering uncertainties and flexibility;
- Both exogenous (customer demand) and endogenous uncertainties (customer satisfaction and process efficiency) have been considered and characterized according to the Geometric Brownian Motion (GBM);
- The consolidation of engineering and financial analyses is achieved through a hybrid real options valuation framework, which is formulated by incorporating the technical and financial real options identified conforming to the PFD configuration process; and
- Appropriate parameters are determined for the valuation in terms of the technical and financial achievements of PFD, so as to avoid confusion from utilizing conventional valuation parameters that do not capture the PFD context properly.

(4) In terms of solution tools for the PFD valuation, the following techniques are employed:

- A numerical options pricing technique (MLTBL) is developed to enhance the consistency, stability, and efficiency of finding numerical solutions for PFD valuation; and
 - A hybrid GA is introduced to enhance the efficiency in selecting the best combinatorial solution for PFD optimization.
- (5) In terms of application to investment decision-making, the flexibility planning framework of product platforms is constructed by extending the hybrid real options valuation framework to the cohort of PFD based on product platforms.
- (6) As for the verification, case studies are conducted to demonstrate the feasibility and potential of the proposed methodology, tools, and application for the vibration motor family design, including identification of real options, valuation of real options, implementation and analysis of MLTBL approach, hybrid valuation of vibration motor family design, implementation and analysis of the hybrid GA, as well as flexibility planning of vibration motor platform investment.

8.3 LIMITATIONS AND FUTURE WORK

Through the case studies, sensitivity analysis and efficiency analysis, the proposed methodologies and solution details have been proven promising in solving the valuation and flexibility planning problems of product family design and platform-based product development. However, certain assumption was used to design the hybrid real options valuation framework. A comprehensive framework with removal of the assumption thus deserves more research efforts. Further, considering more stages and issues in product family development, the avenue of possible future research can be directed as follows.

(1) Integration of competition uncertainty. The hybrid real options valuation framework was proposed with no consideration of the effect of competition, and thus is applicable only in a perfect market environment. However, today's business market is characterized by the intensively dynamic competition, which is caused by the frequent entry and exit of competitive companies. Such market competition has a major influence on investment decision-making. Thus, when making an investment decision, a company should take into account the investment behaviors of the possible competitors. If a company decides to enter a market, the entry may involve a huge sunk investment. In addition, it is possible to bring about large losses to a company if the market is or becomes unfavorable. Further, the company may get embroiled in close competition. In literature, game-theoretic models of strategic market have been developed to model investment decision-making under competitive uncertainty. Therefore, a proper model based on game theory for strategic market evaluation should be developed. Subsequently, a comprehensive valuation framework incorporating the developed model should be designed to address the complex investment problems.

(2) Extension to production configuration. The concept of process platforms is proposed in the production stage of PFD. A process platform relates to a set of design parameters and their value instances that are fundamental to the corresponding product platform (Jiao et al., 2005). The process platform provides a well-structured mechanism for companies to configure optimal production processes (or routings) for new product design that is so called production configuration (Jiao et al., 2005). Similarity and commonality in the set of customized products in a family lead to similarity and commonality in the corresponding routings that are adopted to produce these products. The rationale of production configuration is process similarity and commonality. Process similarity and commonality is exhibited by same or similar operations,

operations sequences, manufacturing resources, and setup activities. Consequently, process similarity and commonality reduce changeovers in family-based production, which eventually lead to an economy of scale in production. Therefore, the future efforts should be made to incorporate production configuration into the proposed methods so that the economies of scale in both design and production can be achieved.

(3) *Customer integration for product families.* The driving force behind product family design and development is the enterprises' positioning of customers at the center of value creation and involving customers into the product fulfillment process. Of primary importance in product families is the interaction with customers (Blecker *et al.*, 2004a). On the technical side, designers have always assumed that customers' satisfaction with the designed product is sufficiently high as long as the product meets the prescribed technical specifications; however, what customers appreciate is not the enhancement of the solution capability but the functionality of the product. This means that the traditional dimensions of customer satisfaction may deserve scrutiny, for example, identifying those product characteristics that cause different degrees of satisfaction among customers; understanding the interrelation between the buying process and product satisfaction; determining the optimal amount of customization and customer integration; explaining the key factors regarding the value perception of customers; and justifying an appropriate number of choices from the customers' perspective.

Equally important are customers' decision-making processes when interacting with product families and in turn developing proper fulfillment capabilities. At the end providing decision support to customers is deemed to be important. This coincides with consumer behaviors in business systems based on customer involvement in the product customization process (Huffman and Kahn, 1998). While most product family-based

customization approaches implemented in practice are based on offering a huge number of variety and choices, the perception of choice and the joy or burden of configuration experienced by customers are not well understood. Many questions are pending. For example, what are the incentives for integrating customers into value creation? What factors drive customers to interact with a configurator? How many variants should be explored and changed before making a final decision? Are there any specific patterns that customers follow when interacting with a product family design system? And how do different levels of the decoupling point (i.e., where the customer is integrated into value creation) influence customer integration and how does this affect the performance of a product customization system? Toward this end, product family development needs to be incorporated with more marketing engineering decisions (Michalek *et al.*, 2005), as well as customer perceptions (Blecker *et al.*, 2004b).

(4) *Collaborative platform for PFD.* With mass customization, the successful proposed framework implementation calls for the correctness of the large information associated with customer needs, design changes, and process variations and the execution of optimal options portfolio and product platform flexibility planning. The result in outdated information often leads to inaccurate portfolio or strategic decision-making. Therefore, a real-time collaborative platform for PFD and product platform management is necessary for effective communication and functional coordination across platform-based product development. Moreover, it is tedious to perform the proposed valuation process. Therefore, a system with user-friendly interface is favorable, so as practitioners can implement the proposed framework much easier without having to rely on outside consultants.

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