# PRODUCT DESIGN AND PRODUCT PORTFOLIO MODELED INTEGRATION AND OPTIMIZATION

by

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# ABSTRACT OF THE DISSERTATION

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by Beverly Veronica Smith

Dissertation Director

Dr. Marianthi G. Ieratpetritou

In this work we developed decision support frameworks that relied on the modeling of multidisciplinary integration to enable the selection of optimal product design alternatives, and to facilitate efficient chemical product design planning and execution.

In recent years, the design of chemical products has received renewed and growing interest, as the industry transitions from a dominant bulk chemical product portfolio to one of high value-add specialty products. This industry shift results from the onset of global competitive pressures accompanied by intense market and consumer demand for improved product quality, lower product cost, shortened development cycle and greater product differentiation. Concurrently, the chemical manufacturers of commodity products are faced with pricing pressures and limited cost reduction options. The existence of these challenging market situations demand the adoption of rapid and efficient product design

approaches that leverage specialized capabilities across disciplines within the chemical enterprise.

The findings from a recent industry benchmark study, conducted as a part of this research, supported the motivation for this work. An assessment of current industry practices involving 15 chemical manufacturers revealed varying levels of organizational maturity as it relates to multidisciplinary and cross-functional leveraging of knowledge in product design undertaking. The chemical manufacturers were evaluated on current practices of integrating consumer preferences, product-process integration and practices of linking business decisions into the product design process. The investigation revealed the absence of formalized frameworks to integrate the critical resources necessary to support optimal product performance and design process execution.

In this study, the set of decision support procedures formalize the interaction between product design and product portfolio decision making by integrating critical elements of both domains. Hence the methodologies incorporate structural framework to forge strategic alignment while optimizing domain interaction in order to minimize cost, reduce cycle time and to determine the optimal product design alternative. Embedded industry case studies illustrate the application of the proposed methodologies which utilize a hybrid approach, involving the application of structural frameworks for domain integration, along with Monte Carlo Simulation and algorithmic processing to optimize the product design planning and execution process.

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# DEDICATION

This work is dedicated to my niece, Leanne Samantha Williams and should serve as a testament to perseverance – A commitment to complete whatever task you have started.

To my mother, Hortense, for instilling the virtues of personal strength and perseverance- in the face of incredible difficulties.

*"It is God that girdeth me with strength, and maketh my way perfect."* Psalms 18:32

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# Chapter 1

# INTRODUCTION

In today's global economy, chemical manufacturers are facing increasingly complex challenges resulting from pricing pressures, intense competition, rising material costs and fluctuating market condition. Furthermore, because of excess manufacturing capacity, pricing of most industrial chemicals remain at commodity levels. Against this backdrop, companies are constantly seeking to identify initiatives and strategies that will enable them to sustain growth and improve their profit margins. Beyond these economic pressures, companies face added demands due to rapid technological changes, such as the evolution in combinatorial chemical synthesis with the use of nano and micro technology (Charpentier 2009). These economic and technological changes are accompanied by intense market demand for speed and product differentiation (Charpentier and McKenna 2004; Hill 2009). Hence, the combination of these prevailing factors has driven the Chemical and related industries to transition to a product portfolio of high value-add specialty products with an accompanying commitment to product differentiation and to finding new market applications. This commitment is fueled by increasing consumer demand for products with specific end-use properties, and also by competitive pressures faced by the process companies (Charpentier and McKenna 2004). Nevertheless, the industry shift from bulk commodity chemicals to high value-add specialty products portfolios creates unique challenges for the engineering design and business communities alike. The new market situation creates new demands on existing product design and product development approaches; in that, such efforts must directly account for the combined market and business demands for shortened lead times, robust product performance and cost effective product differentiation. Moreover, in contrast to commodity chemicals, specialty chemicals are more susceptible to performance measure variability, resulting from the lack of standard performance indices or quantitative methods for evaluating in-process and end-use quality factors. These drivers have created a demand for an efficient product design framework that ensures that optimal product performance is achieved at a minimal cost.

As illustrated in Figure 1.1 the chemical product design problem starts with a basic definition of the product requirement (s), and sets out to identify a chemical candidate that satisfies a specified set of properties along with their target values and/or ranges. The chemical candidate may be a mixture, a single chemical or a formulation of active ingredients and additives (Ng, Gani et al. 2007).

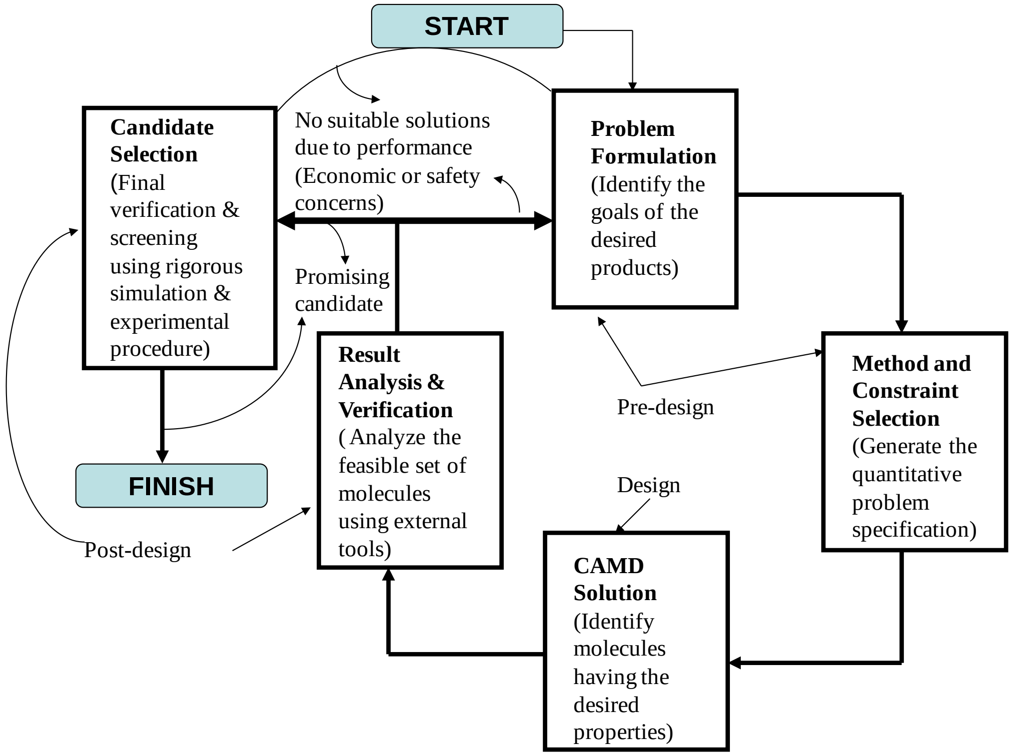



Figure 1.1: The Cyclic Process of Chemical Product Design (Gani 2004)

In this study we focus on a class of chemical products that is central to the new trend of an increasing dominance of value-added products for the consumer market. These Chemical-based consumer products have complex functionalities and may include products such as specialty coatings, detergents, personal care products, cosmetics, paints and pharmaceutical drugs. The general optimization formulation for the chemical product design problem is given as:

$$
\begin{aligned}
&\min_{x} \ \mathrm{Z(x)} \\
&\textit{Subject to:} \\
&h_i(x) = 0,\ i = \{1.....I\} \\
&g_j(x) \le 0 \ \ j = \{1......\mathrm{J}\} \qquad (1.1) \\
&x^L \le x \le x^U \\
&x \in X
\end{aligned}
$$

where $\boldsymbol{x}$ is the vector of design variables, such as composition variables; Z$\boldsymbol{(x)}$ is the performance or cost objective function; I, and J are the number of product design equality constraints and product design inequality constraints respectively. $x^L$ and $x^U$ are upper and lower bounds for the design variables respectively.

The objective of this work is to develop practical decision support systems that will enable efficient product design planning and optimal product performance specification development. The proposed decision support methodologies rely on interdisciplinary integration that is forged by exploiting underlying dependencies between product design and aspects of business operations, as illustrated in Figure 1.1.

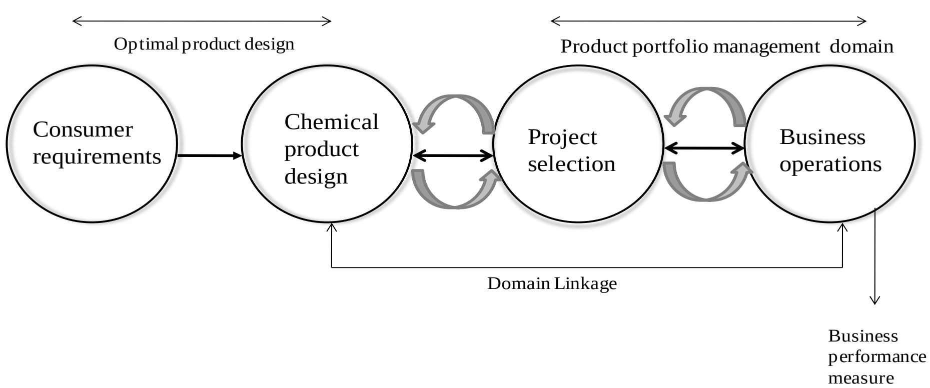



Figure 1.2: Outlay of Product Design –Product Portfolio Integration System

## 1.1 Background and Significance

A review of the recent history of the chemical processing industry (CPI) has revealed a pattern of societal demand followed by product growth and corresponding technology and process adaptation. For example, the period of 1950 to 1970 has witnessed a dramatic growth in the production of synthetic textile fiber that has led to greater production efficiency and the development of computer-optimized design (Moggridge and Cussler 2000). The authors further observed that in more recent times the market and the larger society have imposed new and greater demands on the industries within the chemical sector that has led to cost cutting measures such as ongoing restructuring and rationalization. However, over the years these companies have come to recognize the limitation of these measures during their quest to achieve sustained profitability. Having exhausted some of the classic cost cutting measures, companies operating within the chemical and related industries now face the crucial options of 1)departing the chemical business altogether 2)focusing exclusively on commodities and 3)concentrating on higher value-add specialty chemicals (Moggridge and Cussler 2000). Increasingly companies are opting for product line expansion to include high value-add specialty products because of the upside potential. However, the absence of standard frameworks to support efficient product development of these complex specialty products, coupled with the lack of theoretical predictive models to quantifiably assess their performance in the marketplace often create challenges for the manufacturers. Furthermore, an emphasis on product design necessarily focus on initial decisions concerning the form of the product and implicitly lessens the emphasis on manufacturing (Moggridge and Cussler 2000). Hence, the resulting change in focus from compositional specification to product end-use performance requires greater customer participation in the product design effort to ensure increased chance of product success. Additionally, the resulting growth in chemicals in the marketplace creates an auxiliary challenge due to product portfolio expansion and the derived management complexities. The chemical industry has witnessed an expansion of less than 2 million molecular compounds in 1953 (Charpentier and McKenna 2004) to over 14 million in 2005 (Charpentier 2009).

In this study, we consider that one way to address the increased demand for product development speed and enhanced performance is to identify critical multidisciplinary synergies that can be leveraged to yield enhanced system efficiency. Hence, we focus on the integration of product design and product portfolio management as an effective strategy to secure optimal technical and economic performance.

### 1.1.1 Interdisciplinary Approaches

Over the past decades several studies involving multidisciplinary integration have recorded measurable improvement to the overall product development process (Luo, Kannan et al. 2005). Some of the benefits recorded include improvement in product performance (Griffin and Hausser 1992; Olson and Wagner 1992) reduction in development cycle time (Griffin 1997; Saiedian and Urban 1997; Sherman, Berkowitz et al. 2005) and overall company and market performance (Griffin and Hausser 1996; Gemser and Leenders 2001; Tatikonda and Montoya-Weiss 2001). In more recent times, there have been many approaches proposed for linking engineering design to marketing and other business processes (McAllister and Simpson 2003; Georgiopoulos, Jonson et al. 2005; Michalek, Feinberg et al. 2005; Besharati, Luo et al. 2006). Many of these coordinated approaches offer one-sided support to the enterprise level decision maker but fail to assist engineering design activities and therefore creating sub-optimal solutions to the enterprise wide problem. (Besharati, Luo et al. 2006), presented an integrated design and marketing approach to facilitate the generation of an optimal robust set of products design alternatives to advance to the next stage of the product development process. (Ng 2004) offers a qualitative framework that sequentially links business decision making to product and process design. The hierarchical framework proposed by (Ng 2004) accounts for length and time scales associated with the different levels of decisions making within the enterprise. In this construct, the opportunities for interaction in decision making only exist wherever there are overlapping of the different length scales. However, according to (Georgiopoulos, Jonson et al. 2005), a better approach to linking technological requirements with business decisions, involves quantifying the interdependence between both. To quantify the linkage between technology and business planning, (Georgiopoulos, Jonson et al. 2005) employed a simple financial model and an engineering simulation model to obtain resource allocation solution in product development.

## 1.2 Product Design and Portfolio Management Integration

Product design is a critical stage within the product development process, and one that involves a series of activities that result in product performance and manufacturing process specifications. In general the product design process involves a series of linear steps as shown in Figure 1.3.

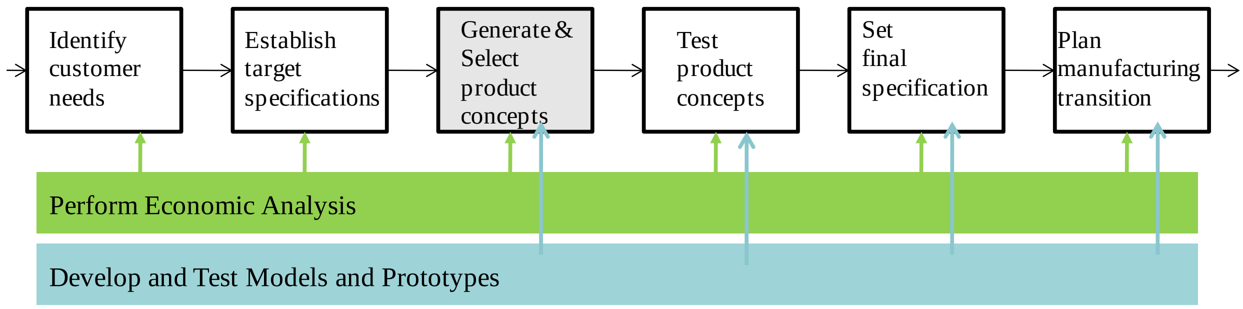



Figure 1.3: General Product Design Process ( Adapted:(Ulrich and Eppinger 2000) )

However, the product design process can also be characterized by a set of decisions that are made in order to satisfy both technical and economic requirements for a given product (Gurnani and Lewis 2008). Among the critical decisions to be made during the design process, are decisions concerning the selection and prioritization of design tasks and the selection of variance reduction or noise control strategies, in the case of robust design application. A method that formalizes critical input from the business' portfolio decision makers to the product design team is expected to help the product design decision making process. Conversely, in research and development (R&D) organizations, the ultimate decision concerning new product investment is made within the context of a new product portfolio.

New product portfolio management is a dynamic decision making process involving the evaluation, selection and prioritization of product development projects (Cooper and Edgett 2003). Such decisions ultimately determine the set of design concepts that advance to the next phase in the product development life cycle, and eventually enter the marketplace. The discipline of product portfolio management has grown in importance in recent decades, as firms seek to respond to an increasing demand for shorter product life cycles heightened by global competition and rapidly changing technologies (Cooper and

Edgett 2003). Moreover, the authors attributed many of the difficulties encountered in new product efforts to ineffective portfolio management. On the other hand, in an earlier study, (Balachandra, Brockhoff et al. 1996) suggested that the difficulties encountered in portfolio decision making are linked to issues that exist at the project (product) level. These factors underscore the importance of portfolio management to product design efforts and therefore to the overall firm's performance. Dynamic and intense market demand has also contributed to the creation of complex product portfolios with unique and enhanced challenges associated with imbalanced portfolios. These new challenges have led to failure in product portfolio management (Cooper and Edgett 2003). Other research studies have also suggested that business reactions such as over-emphasis on speed-to-market, short term preoccupation and overloading of projects have led to portfolio management challenges and eventual product failure (Mikkola 2001).

In this study we seek to isolate the points of integration between aspects of portfolio management and product design by making the distinction between operational portfolio management and strategic portfolio management. Operational portfolio management is primarily concerned with current process efficiency, and is therefore evaluated at the point of execution of product design and product development activities. Strategic portfolio management is forward looking and concerns process effectiveness and its relation to future business performance. In this study we explore the relationship between operational portfolio management and product design decision making while evaluating the impact on the strategic layer of the portfolio management process. According to (Perks 2007), in the past, a number of research studies have focused on improving inter-functional integration at the product level (Kahn 1996; Kahn and McDonough 1997). However, there has been relatively little focus given to the nature of inter-functional integration at the product portfolio level (Perks 2007). Several other studies have pointed to the importance of integration between portfolio level resource allocation and allocation at the project level (Cooper, Edgett et al. 1998; Cooper, Edgett et al. 1999). However, according to (Perks 2007), this area has not been sufficiently investigated. Consequently, one acknowledges that there is a need to focus development on methodologies to facilitate efficient and effective coordination between product design decision making and product portfolio management decision making. A schematic of the proposed "enterprise wide" integration model is presented in Figure 1.4

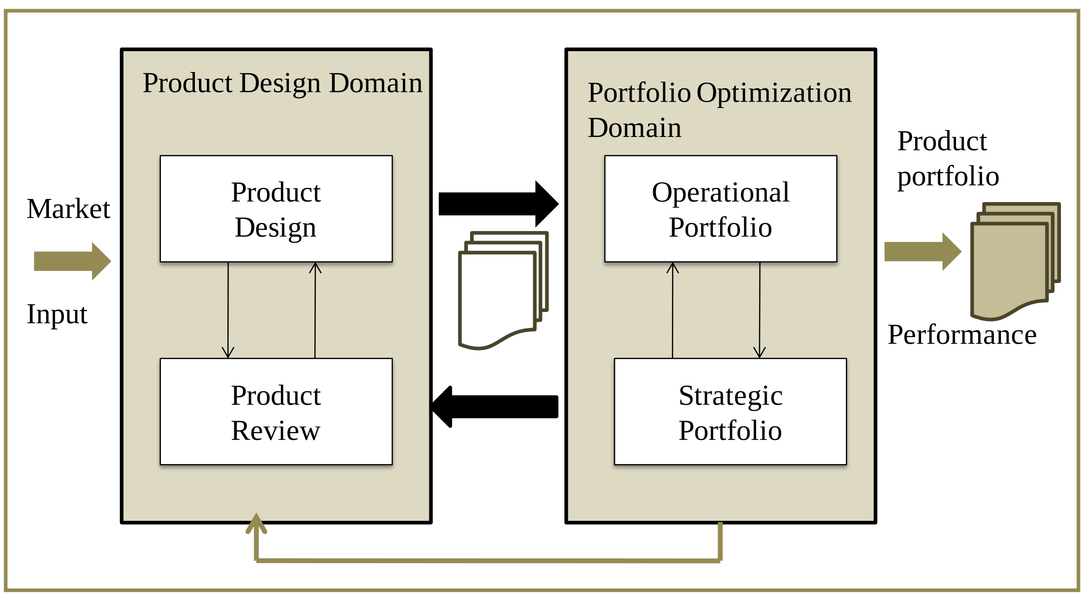



Figure 1.4: Schematic of the Enterprise-wide Integration Model

Figure 1.4 illustrates the elements of the product design domain and the new product portfolio management domain at the enterprise level. Integration activities between both domains are indicated by the directional arrows depicting two-way integration. Thus, optimal design and investment decisions are obtained by simultaneously satisfying both business and technological requirements. This planned integration minimizes the number of unplanned iterations between these two domains while enabling tradeoff between product performance requirements and the business aspects. More importantly, reduction in the number of iterations leads to reduction in development costs and faster time to market. The subject of product design-portfolio management domains integration requires *a priori* treatment of significant aspects of the product design and portfolio management as separate problems. Consequently, description of pertinent areas, related to specific domain, forms a major part of this thesis.

## 1.3 Product Design Optimization

A modification to the general product design optimization formulation explicitly integrates aspects of the product portfolio valuation consistent with a focus on product end-use properties.

A general deterministic formulation for the chemical product design problem is shown in problem (1.2) to include consideration of end-use requirements:

$$\begin{aligned}
&Min\ Z = C^T y + f(x) \\
&S.T. \\
&h_i(x,y) = 0,\ i = 1.......I \\
&g_j(x,y) \le 0,\ j = 1.......J \\
&y \in (0,1) \\
&x^L \le x \le x^U
\end{aligned} \tag{1.2}$$

In problem (1.2), $C^T y$ is the cost associated with the selected product attributes*, f(x)* is the cost associated with the process design variables, $x$ is a vector of continuous design variables, y is a vector of binary variables indicating the existence of a product attribute or the existence of an attribute above a predefined value, the set of equality constraints, $h_i(x,y)=0$, relates to process design specifications, process model equations and properties of the formulated product. The set of inequality constraints, $g_j(x,y)\le 0$, relate to process and product specification.

The optimization problem as presented in (1.2) searches for the optima of the function *Z* of *n* real continuous design variables $x=(x_1,x_2....,x_n)\in X\subseteq\Re^n$ subject to a set of equality and inequality constraints. Formulation (1.2) can be either a mixed integer linear programming (MILP) problem or a mixed integer nonlinear programming (MINLP) problem depending on whether any of the functions *Z(x,y), h(x,y) or g(x,y*) is nonlinear, given {y} is nonempty. In a deterministic optimization the feasible space is defined by all the points that satisfy the constraint equations, and in such formulation, global optimality is only assured if all possible design candidates were considered in the generation of the feasible set. Furthermore, the challenges encountered in determining the global solution of the MINLP problems are well documented in the literature (Murty and Kabadi 1987), (Pardalos and Schnitger 1988). The potential for the existence of multiple local solutions are characteristics of these MINLP problems which are generally nonconvex problems (Floudas 1995). Moreover, MILP and MINLP problems are precisely difficult to solve because of the combinatorial nature of the *y* domain (Floudas

1995). An increase in the number of binary variables ($y$) yields an exponential increase in the 0-1 possible combination of these variables. The resulting large combinatorial problem presents complex analysis such as to characterize the MINLP problems as NP-complete. Known methods for solving MINLP problems include Branch and Bound (B&B), Outer Approximation (OA), Extended Cutting Plane methods and Generalized Bender's Decomposition (GBD). One of the main objectives of the B&B method is to avoid enumeration of all possible 0-1 combinations of the $y$ variable (Floudas 1995). The B&B method begins by considering the relaxed form of the original mixed integer problem (MIP) with the complete feasibility region. Relaxation of the MINLP is commonly attained by dropping the integrality requirement on the $y$ variable and allowing it to be continuous (i.e. $0 \leq y \leq 1$). The original problem is referred to as the root node in the binary tree representation of the branch and bound algorithm. If an optimal solution is not found at the root node, the algorithm is applied recursively to successive sub-problems until an optimal solution is found. Both OA and GBD algorithms decompose the MINLP problem into NLP sub problems and a linear MIP master problem. Hence both of these algorithms require successive solution of a related MIP problem. The main difference between GBD and OA is in the definition of the MIP master problem. OA relies on the linearizations of the nonlinear objective and constraints, thereby reducing each sub-problem to a smaller feasible set. Conversely, the master MIP problem generated by GBD is given by a dual representation of the continuous space. Both OA and GBD algorithms function by generating an upper bound and a lower bound on the MINLP solution obtained for each iteration. The generated upper bound and lower bound are found to be non-increasing and non-decreasing respectively, and eventually converge within $\varepsilon$ in a finite number of iterations (Floudas 1995). According to (Bussieck, Drud et al. 2003) the approaches described above only guarantee global optimality under (generalized) convexity. As such, global optimization of non-*convex* problems, obtained by employing deterministic algorithms, requires the solution of sub-problems via *convex* relaxations of the original problem in a branch and bound context (Bussieck, Drud et al. 2003). The limitations and challenges of specific algorithmic processing approaches were considered during this research study.

The primary focus of this work is the development of a set of product design decision support systems for real world application. The set of decision supports formalize the interaction between product design and product portfolio decision making by integrating critical elements of both domains. Hence, the integrative approaches are aimed at obtaining optimal product performance and greater efficiency in product design planning. Embedded industry case studies illustrate the application of the proposed methodologies. These methodologies utilize a hybrid approach, involving the application of structural frameworks for domain integration, along with Monte Carlo Simulation and algorithmic processing to optimize the product design planning and execution process.

The dissertation is structured as follows. An examination of the application of integrative product design solution strategies is the subject of chapter 2. The findings from the review of the academic literature were supported by an industry benchmark study involving 15 chemical manufacturers. The combined findings from the literature review and the industry benchmark study established the current levels of development and practice within the chemical industry and formed an important motivation for this work. In chapter 3 we introduced a comprehensive framework to facilitate the integration of consumer's influence into the design space using a multi-objective optimization approach. With a focus on end-use product performance, efficient integration of consumer's input is a critical requirement for optimal design selection and trade off considerations. Modeling and optimization of the product design and portfolio management interaction is presented in chapter 4. The proposed model framework utilizes the dependent relationship between product design decision making and product portfolio decision making to aid product design planning and design execution. Similar design planning objective was achieved in chapter 5 by relying on underlying sensitivities between the product design decisions and portfolio management evaluation criteria. A summary of the work and recommendations for future work is presented in chapter 6.

# Chapter 2

# INTEGRATIVE CHEMICAL PRODUCT DESIGN STRATEGIES: REFLECTING INDUSTRY TRENDS AND CHALLENGES

A review of integrative product design strategies is motivated by current trends and challenges faced by the chemical processing industry. The transition in the chemical process industry towards more complex formulated and structured products challenges existing approaches and scientific tools that are well suited for bulk chemical design and properties estimation (Favre, Marchal-Heusler et al. 2002; Charpentier and McKenna 2004). Moreover, the ensuing market challenges, brought on by dominant global trends, demand efficient product design approaches that seek to balance technical specifications and market requirements with the business performance objectives. Integrative approaches to product design are therefore repositioned as useful strategies that simultaneously enhance technical performance and efficiency in design execution. The discussion of the integrative product design strategies in this chapter is based on the findings of a recent industry benchmark study involving 15 chemical manufacturers.

## 2.1 Introduction

General reference to the term “chemical products” in this chapter includes all categories of goods produced by the chemical and related industries. However, primary classification differentiating bulk commodity chemicals from specialty chemicals highlights differences in market influence, and also signals the recent shift within the chemical industry towards higher value-add products. According to Favre et al. (2002), one practical distinction between bulk commodity chemicals market and specialty chemical market is that the latter emphasizes product quality and performance while the former pays particular attention to product pricing. Further classification of these chemicals and chemical-based products elucidates the design solution approaches and highlights the requirement for multidisciplinary integration and non-traditional collaboration between the engineering and business communities.

Chemical product design involves the undertaking that yields the set of product performance specifications necessary to satisfy unique customer requirements. Such undertaking involves “defining customer needs, the generation and selection of design alternatives, determining appropriate product properties and specifying the corresponding process requirements”(Cussler and Moggridge 2001). Consequently, the chemical product of interest may be a mixture, a formulated product containing active ingredients and additives or a single chemical(Ng, Gani et al. 2007). For centuries the dominant staple of the chemical processing industries has been bulk commodity chemicals, such as benzene and ammonia, with the attendant focus on methodologies of process design and process optimization. However, in the face of an increasingly competitive and dynamic global marketplace, the chemical processing industry is responding to the demand for application–specific products that offer high added-value to the customer. Hence, the growth of specialty chemicals and the expansion of the industry's product portfolio to include consumer-based configured products reflect shifts in the chemical process industries (Costa and Moggridge 2006). In a recent benchmark study involving 15 chemical manufacturers, we assessed the impact of current trends on new product development activities within the chemical industry. Figure 2.1 provides a breakdown of the current industry trend drivers along with percentages indicating the relative impact of the individual trend on firms' performance. The data revealed that increased competition due to globalization, market demands for product variety and time-to-market pressure pose great challenge to product development firms within the chemical industry.

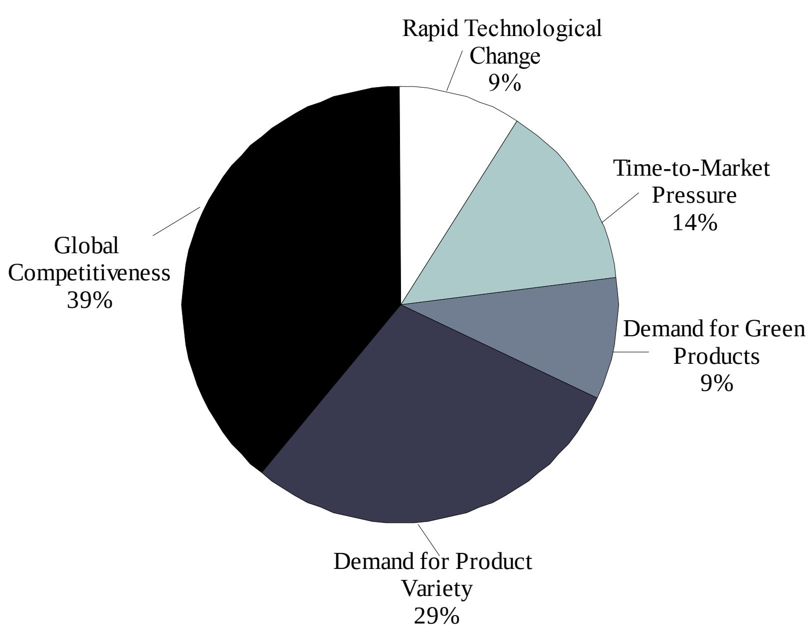



Figure 2.1: Drivers (Trends) of New Product Strategies within the Chemical Industry

The business impact resulting from these industry trends are reported by leading business performance indicators as shown in Table 2.1. The overall impact of these trends is rated by the severity on each category of performance associated with product development and management. The leading business performance indicators are ranked from 1 to 4; wherein a ranking of 1 indicates the business performance measure indicator most affected by the overall industry trend for the given product segment category. The difference in assigned rank between the primary categories of bulk chemicals and specialty products highlights the difference in market-based priorities and the firms' product portfolio strategies.

**Table 2.1: Rank of Performance Indicators by Product Segment**

| *Business Performance Indicators* | *Bulk Chemicals* | *Specialty high value product* |
|---|---|---|
| Product development cost | 1 | 1 |
| Development cycle time | 3 | 2 |
| Product risk | 2 | 3 |
| Product portfolio complexity | 4 | 2 |

The industry trends has delivered a new emphasis on chemical product design, and has correspondingly focused greater attention on processing operations such as granulation, emulsification and coating applications (Favre, Marchal-Heusler et al. 2002). An extensive historical perspective on the chemical process industry is the focus of the work undertaken by (Favre, Marchal-Heusler et al. 2002), which will not be repeated here.

The shift in the chemical industry has also expanded the traditional bounds of chemical engineering application, in that; chemical product design incorporates market requirements along with environmental and processing concerns (Charpentier and McKenna 2004). However, the authors further illustrate that the enhanced complexity extends beyond multidisciplinary requirements to include more complex chemicals, in terms of their molecular structure, when compared to traditional industrial chemicals. Hence, the increase in market demand and intensity has influenced the design of molecular system towards delivering specific end-use product requirements (Favre, Marchal-Heusler et al. 2002). Furthermore, the development of complex product formulation is accompanied by the adaptation or design of processes that can handle such complex structures (Favre, Marchal-Heusler et al. 2002). The transition in the chemical process industry towards more complex formulated and structured products, challenges existing approaches and current scientific tools that are well suited for bulk chemical design and properties estimation (Favre, Marchal-Heusler et al. 2002; Charpentier and McKenna 2004). Moreover, the ensuing business challenges brought on by dominant global trends demand innovative product design solution approaches suited by the individual product segment.

Against an examination of the trends, opportunities and challenges encountered within the chemical and related industries, the chapter explores product design solution strategies appropriate for three major chemical product classifications. In section 2.2 we review design solution approaches of three different classes of chemical products. This is followed in section 2.3 by a discussion on integrative product design solution strategies based on recommendations from a recent industry benchmark study.

## 2.2 Classification of Chemical Products and Their Design Solution Approach

"Product design is linked to product performance much the same way process design is linked to process performance" (Ng, Gani et al. 2007). In general, the product design process begins with an understanding of the product's functional and quality requirements. The product design operation involves steps leading to the identification of a chemical candidate along with a suitable manufacturing process that yield the desired product properties while satisfying a set of economic and processing constraints (Ng, Gani et al. 2007).

Important classification of chemical products leads to appropriate specification of the product design elements and the overall design approach. An example of such product grouping was offered by Seider et al. (2009), in which chemical products were classified as basic, industrial and configured consumer chemicals respectively. Such group labeling of chemical products hints at the targeted market and the product's end-use application. In other works, product classification such as structured products or formulated product (Ng, Gani et al. 2007; Hill 2009) provides insights concerning the design solution approach and the product's formation. In other instances, primary differentiation made between functional chemicals and chemical-based consumer products (such as drugs and cosmetics) implies differences in processing requirements and levels of end customer categories. Hence, functional chemicals often serve as intermediate chemicals used in the manufacturing of chemical-based consumer products (Ng, Gani et al. 2007). In the sections that follow we review three types of chemical products and their corresponding design trends and challenges.

### 2.2.1 Basic / Functional Chemicals

In general, the design of the basic or functional chemicals, such as organic solvents, involves iterative generation and testing of candidate molecules or mixtures in an effort to identify the candidate that yield the desired properties (Ng, Gani et al. 2007) . The design of basic products exploits the molecular structure–properties relationship in order to achieve the desired performance. For example, the design of basic polymeric products relies on the control of molecular weight distribution (MWD) to secure the desired mechanical and rheological properties for specific product applications. In a recent study, Chen et al. (2009) target specific molecular weight distribution of a polymer product by optimizing the initiator and temperature profile to attain the end-use specification.

The application of computer-aided technique in molecular design for basic chemicals has offered greater efficiency when compared to traditional approaches such as database searches, benchscale synthesis and testing (Sahinidis, Tawarmalani et al. 2003; Siddhaye, Camarda et al. 2004). However, the application of computer-aided technique is not trivial, since the efficacy of such optimization approach can be limited by computationally intensive enumeration techniques, deployed to evaluate all molecule/mixture combination (Churi and Achenie 1997). Furthermore, the use of nonlinear complex property prediction models leads to multiple local optima and likely suboptimal solution (Sahinidis, Tawarmalani et al. 2003). However, the solution of molecular design problems modeled as mixed integer nonlinear problems has been extensively researched over the past decades(Churi and Achenie 1997; Ostrovsky, Achenie et al. 2002; Ostrovsky, Achenie et al. 2003; Karunanithi and Achenie 2005). In a recent study, Sahinidis et al. (2003) proposed the application of a formulation that includes novel structural feasibility constraints coupled with a suitable branch-and-reduce algorithm to obtain global optimal solution for the general molecular design problem. The mathematical formulation for the general molecular design problem was given as (Sahinidis, Tawarmalani et al. 2003):

$$\begin{aligned}
&\min_{x,n} f_{obj}(x,y) \\
&\textit{Subject to}: \\
&g(x,y) \le 0 \\
&x \in \Re^m, n \in N
\end{aligned} \qquad (2.1)$$

where $f_{obj}(x,y)$ is the objective function represented as a product performance index or an economic term to be minimized or maximized (e.g. profit, cost), $g(x,y) \le 0$ is the set of structural and property constraints, $x$ is the vector of continuous variables such as mixture composition, $y$ is the vector of integer variables (binary variables) used for selection of discrete molecules, groups or atoms. By accounting for the process performance in the design problem, Equation 2.1 is modified as follows:

$$
\begin{aligned}
&\min_{x,n} \tilde{f}_{obj}(x,y) \\
&Subject\ to: \\
&g(x,y) \le 0 \\
&h(x,y) = 0 \\
&x \in \Re^m, n \in N
\end{aligned}
\tag{2.2}
$$

where $\tilde{f}_{obj}(x,y)$ is the integrated product-process performance objective and $h(x,y)=0$ is the set of process model constraints. The continuous variable **x** concerns product properties and process variables such as temperature or flow rates. The integer variable **y** accounts for the selection of the product component as well the selection of process units. As pointed out by (Ng, Gani et al. 2007), there are instances involving mixture design where there exists no need for process constraint considerations. Such is the case in the design of solvent mixtures and petroleum blends (Ng, Gani et al. 2007). In molecular design applications the optimization limitations have been mitigated by use of various approaches. For example, the issue of multiple local optima was addressed by applying interval arithmetic techniques to create interval relaxation in molecular design applications (Joback and Stephanopoulos 1990; Joback and Stephanopoulos 1995; Vaidyanathan and El-Halwagi 1996). A modified branch and bound algorithm was applied to models in which the number of linear constraints exceeded the number of non-linear constraints (Ostrovsky, Achenie et al. 2002; Ostrovsky, Achenie et al. 2003). Unlike conventional branch and bound approach, the branching activities occurred in a reduced space created by using branching function instead branching on all search variables (Ostrovsky, Achenie et al. 2002; Ostrovsky, Achenie et al. 2003). Limited search obtained by the use of stochastic search techniques applied to sampled regions of the search space that have high probability of good solutions (Devillers and Putavy 1996; Ourique and Telles 1998; Marcoulaki and Kokossis 2000a; Marcoulaki and Kokossis 2000b; Venkatasubramanian 2005). However, there still exists the major challenge of predicting properties of compounds when required to apply optimization techniques (Balasubramanian and Grossmann 2004). According to Ng et al.(2007), a combined computation and experimentation approach is followed when designing larger complex chemicals, such as the active ingredients (AI) used in consumer products or pharmaceutical drugs. Experimentation (and property measurement) approaches are pursued when there are no mathematical models available for property estimation (Ng, Gani et al. 2007). However, the time-consuming and expensive nature of experimentation limits the number of product candidates that can be investigated.

In spite of the challenges and industry trends towards specialty products, the design of molecules and mixtures with desired properties continues to be an expansive field as it finds application in the design of novel polymers and other chemical products. However, as revealed from the recent benchmark study, the basic chemical product category has not escape the market pressures brought on by global competition and rapid technological changes. Consequently, there exists even greater demand for cost containment resulting in the need for innovative strategies for enhancing product design efficiency beyond the application of efficient search techniques or effective experimentation strategies.

### 2.2.2 Structured Products

The design of structured products requires a solution strategy that considers the manufacturing process contribution to the final product properties (Ng, Gani et al. 2007; Hill 2009). In this instance, the control of the product's end-use properties is governed by the microstructure of formation(Ng, Gani et al. 2007). Moreover, according to Ng et al. (2007), this class of products combines many properties and functions into a single product, and therefore relays a higher level of design complexity when compared to basic chemicals. Various studies have proposed a systematic approach to designing structured products(Meeuse, J. Grievink et al. 2000; Wibowo and Ng 2001; Wibowo and Ng 2002; Hill 2009; Smith and Ierapepritou 2009) while carefully highlighting the limiting utility of these approaches due to unique product requirements. However, such proposed methods contain the common elements of determining up front product performance requirements, the generation and evaluation of product design alternatives, followed by the selection of an optimal design (Hill 2009). The design of cosmetic product, such as skin care cream, has been the subject of numerous research studies in recent times(Wibowo and Ng 2001; Wibowo and Ng 2002; Cheng, Lam et al. 2009; Smith and Ierapepritou 2009). For example, in a recent study to design an under eye cream product, Smith and Ierapepritou 2009) applied a multiobjective mixed integer optimization approach to generate a pareto optimal set of product design alternatives. The "most preferred" design was selected from this pareto set based on appropriate design tradeoff considerations. In other studies, Chen et al. (2009) expanded the product design problem to include aspects of product development such as marketing and project management inputs. The skin care cream case study illustration included in this study, provide insights on the interdisciplinary collaboration and challenges that accompany such development efforts (Chen, Chen et al. 2009). For example, changing market demands may challenge the capability for an appropriate or timely product design response (Chen, Chen et al. 2009). The seminal work undertaken by Wibowo and Ng (2001); (2002) also offers a comprehensive review of the technical challenges encountered in the design and manufacture of structured products. The performance of such structured products are evaluated based on its functional properties and a set of quality related attributes, commonly referred to as quality factors (Wibowo and Ng 2001). Hence, one of the challenges associated with these structured products involves quantifying the relationship between sensory quality attributes (Wibowo and Ng 2001) and the product's structural and material properties.

The proposed combination of psychophysical models (Breuer 1983), experiential heuristics (Wibowo and Ng 2001) and predictive physical models still offers less than robust solution to the overall design problem. This is due to the fact that the use of arbitrary scales to quantify sensory quality factors (Wibowo and Ng 2001) maintains elements of inherent subjectivity. Furthermore, the design of many structural products relies on trial and error experimentation approach or a hybrid model-based experimentation approach because of a lack of predictive mathematical models that adequately describes the relationship between the product's performance and the process and material variables (Wibowo and Ng 2002; Cheng, Lam et al. 2009). For example, in a recent study to select the optimal cream formulation, Mostefa et al. (2006) applied response surface modeling experimentation approach to determine the optimal composition of mixture excipients and the optimal operating conditions. The characteristic complex media of these structured products present inherent technical challenges associated with the system's stability, along with unique process design and process control issues (Ng, Gani et al. 2007). Moreover, the combined functional requirements of these structured products create additional issues concerning conflicting technical objectives along with potential raw material incompatibility issues(Chen, Chen et al. 2009). Hence, appropriate multidisciplinary consideration, including an integrated product-process strategy, is required when designing these structured chemical products. In addition to these technical challenges, this product category is greatly influenced by ever increasing market forces, such as time-to-market pressure and the need for product differentiation. Consequently, product design strategies that ensure the incorporation of consumer influence, coupled with design process efficiency, play a crucial role in guaranteeing the product's success.

### 2.2.3 Configured-Consumer Products

In this study the classification of configured-consumer products emphasizes the product's design flexibility and the unique chemical-physical technology required for the product's functionality. According to (Seider, Soemantri et al. 2009), configured-consumer products are often manufactured from basic chemicals and industrial chemicals. These products normally target the consumer end-user market (Seider, Soemantri et al. 2009), and therefore require up front consideration of end-use application conditions as important design considerations. (Seider, Soemantri et al. 2009) further likened the properties of the configured products to those used to characterize industrial or structured products, including functional properties (for example adhesion) and quality attributes (for example smell, feel). However, by definition, a configured product may combine several technology platforms in a single product. Hence, the product design efforts involve a wide cross section of technical expertise based on the technology platforms involved (Seider, Soemantri et al. 2009). Examples of configured consumer products include drug delivery patches, medical tapes, post-it notes, integrated circuit (Ng, Gani et al. 2007) and pressure sensitive adhesive label products. The design of a transdermal delivery system (patch) for example, typically concerns a range of materials with specific functional and quality requirements. The basic multilayer drug delivery system consists an outer backing layer, the therapeutic drug, pressure sensitive adhesive layer and a release liner layer (Prodduturi, Glen J. Smith et al. 2009). According to (Prodduturi et al. (2009), the drug that provides the therapeutic treatment may be incorporated in an “inert polymer matrix” or dissolved in solution in order to facilitate drug release and delivery. The outer backing layer provides structural support for the multilayer construction as well as provides barrier protection from the external environment and also provides drug impermeability capability. The pressure sensitive adhesive provides the necessary anchorage to the skin’s surface during product application (Prodduturi, Glen J. Smith et al. 2009); while the release liner provides protection to the adhesive layer prior to product application. Hence, the design question for these types of products addresses the three dimensional product requirements while addressing the unique functional and quality specifications for each product component. In an earlier study, (Woofson, McCafferty et al. 1995) described a novel bilaminar patch design that consist a drug-loaded bioadhesive film bonded to a backing layer formed from thermally-cured polyvinyl chloride emulsion.

In this instance, the design problem accounts for the morphology of the bioadhesive film via the particle size distribution requirements on the casting solvent and bioadhesion properties (Woofson, McCafferty et al. 1995). Other design requirements specify the film's mechanical stability under ambient storage condition and bioadhesive strength controlled by the plasticizer content in casting gel and film thickness. As noted by (Prodduturi et al. (2009); a well design drug delivery system accounts for a robustly defined drug release profile. Hence, the rate-limiting step is identified as the release of drugs from the delivery system in oppose to the absorption of drug into the skin (Prodduturi, Glen J. Smith et al. 2009). In the study undertaken by Woofson, et al. (1995), a comparison of the release profiles obtained by drug penetration via the bioadhesive layer and the backing layer satisfied the impermeability requirements of the backing layer.

Similarly, the product design problem of the pressure sensitive adhesive label materials is characterized by the design of individual materials components, the material components combination along with the specification of the coating and application technology. In general, consumer-based configured products offers design flexibility, thereby allowing firms to respond rapidly to market and technological changes. Hence, inexpensive creation of product variants can be easily achieved by applying different combination of existing or alternate materials. However, material compatibility issues can pose real design challenge, therefore demanding early and active multidisciplinary collaboration throughout the design process. Moreover, the ease of creating product variants can lead to challenges in product portfolio decision making and ongoing portfolio management. Hence, the integration of aspects of technical product design with those of product portfolio management can aid the decision making process in both domains. This integration can lead to enhanced efficiency in product design execution, better resource allocation and portfolio value maximization (Georgiopoulos, Jonsson et al. 2005).

Design considerations for each product category are summarized by the design aspects of product properties, process design considerations and end-use application performance consideration. The design solution approach summary is presented in Table 2.2.

**Table 2.2: Design Solution Approach by Design Aspects**

| | *Product Properties* | *Process Design* | *Application Performance* | **Product Example** |
|---|---|---|---|---|
| **Functional Chemicals** (molecule or mixture) | Based on relationship between molecular structure or mixture blend and desired properties | May or may not consider process model constraint<br><br>Combined focus on product quality and cost constraints | Chemical compatibility<br><br>Environmental impact<br><br>Functionality requirement for intermediates | Solvent (Toluene) |
| **Structured Products** Industrial or consumer based) | Based on relationship between micro-structural properties and product performance | Product centered process design | Product's life cycle & system's stability | Cosmetics (Hand cream) |
| **Configured-consumer products** | Based on relationship between materials, structural properties & combined performance requirements | Integrative and multiple function & technology platforms<br><br>Product-centered process design | Multi-function application with unique application condition requirements | Transdermal drug delivery system ( patch) |

## 2.3 Integrative Product Design Strategies

Time-to-market pressures, combined with a market emphasis on value-add products, demand greater efficiency in product design practices within the chemical and related industries. Practices such as iterative rounds of experimentation, sequential product and process design, *ad hoc* approach towards the undertaking of product design tasks, product over-design directed activities, product design schedule and cost overruns are just some of the common inefficient product design related practices encountered within the industry. Furthermore, in an effort to meet the increasing market and industry demands, firms are consistently seeking to identify ways in which they can better leverage synergies among the disciplines involved in product design, product development and product management. Hung et al. (2008) credit successful and effective product development to the integration of a variety of specialized capabilities and interdisciplinary collaboration through cross-functional teams. However, the authors noted that such complicated interdisciplinary action requires many knowledge input in order to generate a suitable product solution (Hung, Kao et al. 2008). Such collaborations must be supported by standardized streamlining mechanisms in order to maximize the benefits from domain knowledge in this time-competitive environment. Consequently, integrative product design strategies are best executed through standardized approaches aimed at addressing issues of product performance specification and product design scheduling and costing. The general integrative chemical product design methodology given in Figure 2.2 incorporates integrative strategies within the chemical product design problem. Such explicit incorporation encourages full and effective leveraging of multidisciplinary domain knowledge that leads to adjustment of the time and resource requirements for the design planning optimization problem. Furthermore, formulation of the consumer objective forces tradeoff consideration between consumer preference and designer preference; thus increasing the probability of product success. Hence, the product design problem combines the technical performance objectives with the project planning aspects in response to the new market challenge of increased competition, increased demand for speed, shorter product life cycles and a diverse consumer base.

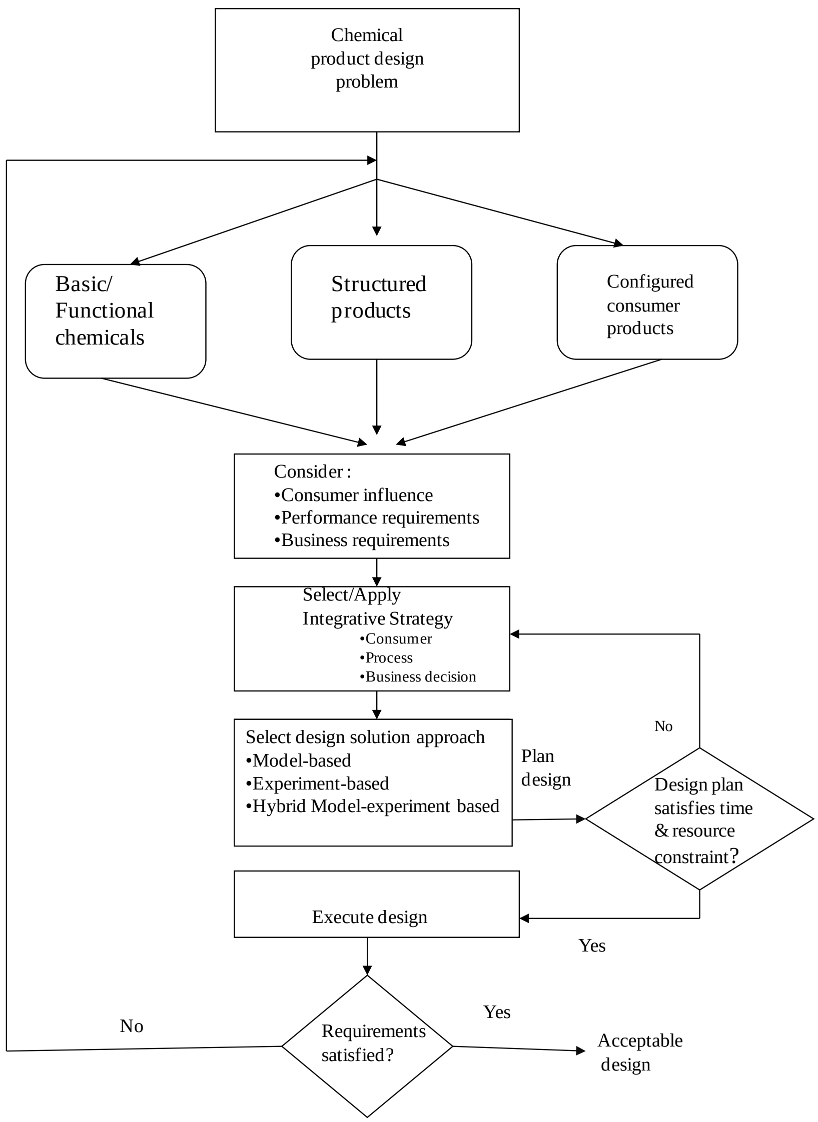



Figure 2.2: Methodology for Integrative Chemical Product Design

A recent investigation of current industry practices indicated varying levels of organizational maturity as it relates to multidisciplinary and cross-functional leveraging of knowledge in product design undertakings. The 15 chemical manufacturers that participated in the benchmark study were evaluated on current practices of integrating consumer preferences, product-process integration practices and practices of linking business decisions (portfolio decision variable) into their product design process. Integrative practice levels were assessed on a scale of 0 to 5 as indicated in Table 2.3.

**Table 2.3: Integrative Product Design Practice Rating Scale**

| | 0. None | 1. Inadequate | 3.Operational | 5.Fully Integrated |
|---|---|---|---|---|
| Integrated Cross-functional Element | Does not exercise this practice | Low level of implementation | Have standardized approach in place but followed inconsistently | Apply standardized approach and practice consistenly |

The results obtained from our study sample have been summarized by chemical product categories as shown in Figure 2.3. These results indicate some level of implementation across all product categories, albeit *ad hoc* and selective in many instances. We note that the integration of the voice of the consumer into product design activities is the most mature of the three integrated cross-functional practices across all chemical product categories. Conversely, the data reflect a notable absence of standard mechanism to facilitate the influence of business decisions on product design activities. Hence, in many instances business decisions are linked to product design decisions in an *ad hoc* manner or for selective product design projects.

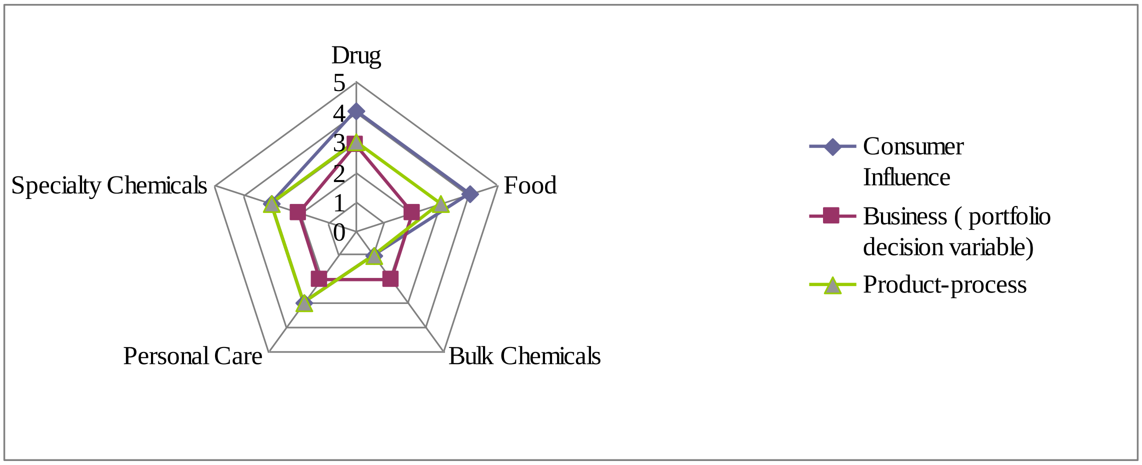



Figure 2.3: Practice Implementation Levels of Integrated Cross-functional Elements

## 2.3.1 Consumer Preference Integration

The process of product design consists of a series of decisions. Such decisions may involve the balancing of conflicting design objectives and ultimately the selection of the design alternative that advances through the development process. According to (Besharati, Azarm et al. 2006), the decision to select a design for a given product is one of the most crucial decisions in the product design and development process. Traditionally, among the factors that influence successful product design are the customer preferences and the designer preferences, as influenced by his/her design issues and market considerations (Besharati, Azarm et al. 2006). With an ever increasing transition to value-add products, integration of the voice of the consumer is playing an even more critical role in the product design process. However, with increased globalization and media influence, the consumer expectations has “grown more diverse, changes more rapidly and has become more sophisticated” (Yang, Jang et al. 2003). Resulting from these challenging trends, firms require efficient and flexible approaches for timely integration of consumer voice in order to be successful (Costa and Moggridge 2006). The recent benchmark study revealed 3 causes of poor consumer voice integration; namely 1)failure to adopt a standard approach 2) disconnect between the point of information capture and point of application (product design) and 3) too much reliance on the historical knowledge possessed by marketing and sales personnel. Faulty assumption concerning consumer needs is one of the primary reasons for missing shifts in the market that leads to eventual product failure or product rejection. Some of the practical challenges to consumer preference integration involve the capture, prioritization and translation of consumer requirement into the product’s functional and quality requirements. The use of “fuzzy” terms in specifying consumer needs coupled with subjective product evaluation approaches often creates difficulty when seeking to specify quantitative design requirements.

For the past decades, Quality function Deployment (QFD) has been recognized as one of the most effective integrative schemes used for capturing market requirements and translating them into technical product specifications (Yang, Jang et al. 2003), (Hung, Kao et al. 2008), (Chan and Wu 2002) . Variants of the QFD technique, such as a QFD-based optimization approach proposed by (Yang, Jang et al. 2003), combines the QFD technique with multi-objective optimization to facilitate tradeoff between multiple customer objectives. Combining of QFD technique with design structure matrix (DSM) adds aspects of product design project planning with product quality as defined by the customer requirements (Hung, Kao et al. 2008). This approach, although limited in its application to modular product, offers a clear linkage between the customer requirements and design planning activities with the inherent flexibility for real time planning adjustments (Hung, Kao et al. 2008).

In a recent study, (Smith and Ierapepritou 2009) proposed a systematic framework that accounts for the unique set of design considerations for the chemical-based consumer products and explicitly incorporate consumer preference. Such integrative strategy relies on a flexible approach that can adapt to changing and demanding consumer requirements as well as to a diverse consumer base.

### 2.3.2 Product-Process Integration

The emphasis on the integration of product and process design issues is a natural outgrowth of the industry's transition towards high value-add structured or formulated products. However, the simultaneous consideration of product and process design is one of the more established integrative practices in new product development or process synthesis. For example, in an earlier work (Jaksland and Gani 1996), utilized an integrated approach that relied on the relationship between the physico-chemical properties, process design and process control to yield an efficient search strategy for the product design problem. The benefits of product-process integration were illustrated in a more recent study undertaken by (Bernardo and Saraiva 2005). The design optimization of a cosmetic lotion example accounted for the product's functionality, the consumer specified quality attributes, the process operating and economic constraints (Bernardo and Saraiva 2005). In this example, the product-process integration optimization problem relied on quantifiable relationship between the product's quality attributes (e.g. product's viscosity) and the composition, as well as relationship between the product structure and composition and the process design. The solution to the integrated product-process optimization problem yielded optimal product composition and process specifications values that were found to be superior to values obtained from a sequential approach of product design followed by process design (Bernardo and Saraiva 2005). Nonetheless, the challenges and issues concerning integrated product–process design applied to structured formulation are well documented in the literature (Gani 2004),(Eljack, Abdelhady et al. 2005).

### 2.3.3 Integration of Business Decision Variables

In acknowledging the widespread integration of biology into chemical engineering applications,(Ng 2004) questions whether the integration of management science will be the next frontier. New product portfolio strategy typically reflects the overall organizational strategy, and dictates resource allocation decisions within the research and development (R&D) function. However, neither strategy provides much guidance to project level decision making or tasks management considerations. The methodology proposed by Ng (2004) offers a hierarchical business decision-making framework, wherein distinct decision-making levels correspond to specific length and time scales. Correspondingly, the decision-making within R&D reflects different levels associated with specific length and time scales (Ng 2004). While there exists logical steps leading progressively from corporate level strategy to marketing strategy, and ultimately to the specification of the process flowsheet, there is also intra-level interactions that are indicated by regions of length scale overlaps. Such overlaps can be exploited to yield greater efficiency in product design. The area of product design project planning and scheduling offers opportunities for enhanced efficiency and better product portfolio coordination as reflected in recent research studies undertaken by (Subramanian, Pekny et al. 2003). Furthermore, according to Georgiopoulos et al. (2005), technical product design should be positioned within an enterprise context in order that the firm reaps maximum economic value. A study to demonstrate linkage between technological decisions and business decisions was undertaken by Georgiopoulos et al. (2005) and was based on the assumptions that the firm's profitability was a function of product design decisions (Georgiopoulos, Jonsson et al. 2005).

By considering the expected economic utility of design decisions designers can appropriately adjust the design problem's feasibility region in such a way that leads to better resource allocation decisions. However, this integration has not been well exploited, in part due to inherent disciplinary boundaries (Michalek, Feinberg et al. 2005), as well as due to the challenge involving quantifying the relationship between business and engineering decisions as indicated by the absence of modeling approaches that suitably bridges both domains (Georgiopoulos, Jonsson et al. 2005). The benefit of obtaining optimal product decisions was offered as the case for integrating marketing and engineering product design decisions (Michalek, Feinberg et al. 2005). In their study, Michalek et al. (2005) utilize the analytical target cascading (ATC) model to quantify the impact of technical engineering decisions on business decision making.

The underlying assumption of domain dependence can be represented in the integrated formulation given in Figures 2.4 and 2.4b. In these formulations, optimal design decisions and investment decisions are obtained by combining technological and investment constraints appropriate for each chemical product category.

| | |
|---|---|
| maximize | technical product performance ( functional or quality) |
| with respect to | economic decisions |
| | design decisions |
| subject to | economic value/ constraints |
| | product specification |
| where | product specification is a function of |
| | quality requirements, property and process constraints |

Figure 2.4a: Product- performance-focused Integrated Formulation :Adapated (Michalek, Feinberg et al. 2005)

| | |
|---|---|
| maximize | business performance ( e.g. profit) |
| with respect to | investment decisions |
| | design decisions |
| subject to | investment constraints |
| | design constraints |

Figure 2.4b: Business-performance-focused Integrated Formulation: Adapted(Michalek, Feinberg et al. 2005)

The formulations given in Figures 2.4a and 2.4b link the business objective to the product design features and properties. Hence the firm's profitability is dependent on product design decisions. Conversely, product design decisions are made within an enterprise context and are therefore weighted based on their utility to the firm (Georgiopoulos, Jonsson et al. 2005). The imposed constraints include resource availability, product and process performance specifications and applicable regulatory requirements. The assigning of economic value or utility to individual product performance objectives assumes an independent relationship between these objectives. Hence, this observation could limit the application of this approach to chemical product design problems wherein there exist dependent relationships among product properties. Additionally, the recent survey study that was carried out among 15 chemical manufacturers identified 5 practical issues that impedes business linkages: 1) The lack of historical data to gauge market preference based on product attributes 2) The lack of common variables between the domains 3) Time-to-market demands undermine the need for full evaluation of product performance scenarios 4) Chronic shortage of resource and 5) Regulatory imposed restrictions limits flexibility to adapt. The success of any organization is largely determined by the quality of its product design execution at the level of project details. Consequently, the goal of the product design procedure is also to deliver a "more efficient and faster design of chemical products that are able to meet market demands"(Costa and Moggridge 2006). Hence, appropriate application of integrative strategies can help to streamline product design activities that can lead to better resource utilization, cost avoidance and shorter product design lead time.

## 2.4 Conclusions

The underutilization of domain knowledge within product development activities is a luxury that the chemical industry can no longer afford. The era of globalization has intensified competition and has generated strong market forces that are now at play within the chemical processing industry. In response to these market forces the chemical industry has transitioned from a portfolio dominated by bulk commodity chemicals to one of high value specialty chemicals. Resulting from these trends and challenges, the product design implications concerns technical product performance as well as product design project planning and management.

The application of integrative product design solution strategies offer an innovative response to the increasing market demands for speed and value, while satisfying business need for efficient resource allocation. Evaluation of the practices of 15 chemical manufacturers revealed varied levels of implementation of consumer voice integration, process models integration and the integration of business decisions within chemical product design activities. However, the absence of credible modeling approaches has limited integrative application to *ad hoc* practices and sporadic implementation. Hence, it would be useful to construct standard frameworks and mechanisms to facilitate such integration.

# Chapter 3

# FRAMEWORK FOR CONSUMER INTEGRATED OPTIMAL PRODUCT DESIGN

The need for rapid product design, resulting from time-to-market pressure, is accompanied by an increasing demand for product differentiation. In order to meet these demands, firms are seeking more efficient ways to integrate consumers input into the product design process. Furthermore, appropriate integration of consumer influence yields the tangible benefit of increased probability of product acceptance in the marketplace. The objective of this chapter is to introduce a comprehensive framework that integrates consumer's influence into the design space using a multi-objective optimization approach. We formulate the problem as a bi-objective mixed integer problem, for which the compromised solution is represented as a set of efficient points. A case study involving optimal design of an under eye cream product was used to illustrate the application of the framework.

## 3.1 Introduction

The emergence of the global marketplace offers unique challenges to the engineering design community and to business decision makers; simultaneously forcing both groups to find innovative ways to respond to new product demands, while ensuring business competitiveness. The increasing need for rapid product design and development, brought on by the dynamics of the global marketplace, is matched by the need for product differentiation through greater product innovation. However, as competition increases firms are finding it even more difficult to differentiate their product's performance and their product offerings. Furthermore, advancements in technology and consumer expectations have driven the development of more complex products with multi-functional requirements (Charpentier and McKenna 2004; Gani 2004). With the convergence of the need for rapid product design and a greater need for product differentiation, firms are constantly seeking for efficient and flexible roadmaps for extracting and incorporating valuable consumer input into their design process.

The chemical manufacturing industry, in particular, is experiencing a shift from the development and manufacture of bulk commodity chemicals to the design and manufacture of specialty high value-added chemical products(Cussler and Moggride 2001). This shift to high value-added specialty products is fueled by an increasing consumer demand for products with specific end-use properties, and also by competitive pressures faced by the process companies (Charpentier and McKenna 2004). This emerging trend implies greater challenge to achieving the desired product quality while keeping cost at a minimum. In a recent study (Bagajewicz 2007) contended that the expansion in the chemical industry to high value-added products, extends beyond molecular design to wider business aspects such as finance and microeconomics. Hence, the chemical-based consumer products (CBCP) design problem ought to incorporate such factors as consumer preference, economic considerations and specific product performance requirements. Furthermore, these design considerations are accompanied by some unique technical challenges, due in part to the (often) poorly understood physical phenomenon of the complex multiphase media, that's inherent to many of these structured chemical-based products (Wibowo and Ng 2001). Moreover, the resulting absence of quantitative predictive theoretical models, and product performance evaluation measures, mandate the application of statistical rigor to quantify product performance and also to ensure the credibility of consumer's subjective evaluation. Ng et al. (2007) identified other prevailing issues concerning chemical product design; these include: 1) "the need to define a chemical product in terms of a set of desired properties 2) determining a set of product candidates that define the search space in which the optimal product may be found 3) determining the process that can manufacture the desired product with the specified quality at the optimal cost and 4) the evaluation of product and process performance." Gani, R.( 2004) further highlighted the need for multi-scale property models and a systems product design framework aimed at reducing design costs and cycle time. According to Hill, M. (2004) the perceived value of these chemical-based consumer products is derived from the product's performance as evaluated by the consumer. Therefore, the consumer needs form the driving force for the product centered industry(Stephanopoulos 2003) and should play a critical part in the product design process. Consequently, the proposed systematic framework explicitly integrates market requirements, in the form of consumer preference, with the firm's economic objective while yielding the desired product's performance. In so doing, the framework incorporates a flexible solution based on the selected multi-objective optimization approach. Furthermore, the framework offers a comprehensive approach to the design of the chemical-based consumer products that enhances efficiency and minimizes the selection of sub-optimal designs. In practical application, the integration of the varied aspects of the design problem forges multidisciplinary collaboration that leads to greater probability of product success and faster time to market.

The chapter is organized as follows. First, a review of the unique set of design requirements for the chemical-based consumer product design problem is presented in sub-section 3.2. A description of the consumer integrated product design framework is outlined in section 3.3 and followed by a case study illustration in section 3.4.

## 3.2 Chemical-based Consumer Product Design

In recent decades the global consumer market for chemical and related products has championed increased demand for improved product performance and shorter product life cycle (Tanguy and Marchal 1996; Pisano 1997; Viladsen 1997; Wintermantel 1999). Consequently, these industries are placing greater emphasis on product engineering in response to the greater market demands for value-added differentiated products (Westerberg and Subrahmanian 2000). In general, the chemical design problem starts with a basic definition of the product's requirements and sets out to identify a chemical candidate that satisfies a specified set of properties and property values (Cussler and

Moggride 2001). The chemical product can be classified as a single chemical with specific properties or a formulation of active ingredients and additives(Ng, Gani et al. 2007) for a specific application. Typically, the chemical-based consumer products are mixtures of active ingredients that provide the functional product attribute, and inactive excipients that further enhance the product's performance (Wibowo and Ng 2002). The design of chemical–based consumer products, such as specialty coatings, detergents, personal care products and cosmetics, can be largely characterized by efforts to satisfy a unique combination of factors. Table 3.1 summarizes the design factors along with their corresponding design considerations.

**Table 3.1: Product Design Considerations for Chemical-based Consumer Products**

| Chemical Based Consumer Products ( CBCP) Factors | Critical Product Design Considerations |
|---|---|
| • End- use product application | • Consumer preference integration |
| • Complex media | • Media micro structure and ingredients /Integrated design |
| • Subjective property estimation | • Measurement source variability |
| • Unavailability of mathematical models for estimating product properties | • Black box analysis applicable for specified system and experimental range |
| • Low volume manufacture | • Inflexible process |
| • Relatively short product life cycle | • Shortened design/development time |
| • Large consumer base | • End-use application variability |
| • Consumer pull | • Active consumer involvement |

The emphasis on end-use application implies the control of end-use property as a primary requirement for designing chemical-based consumer products (Charpentier 2002). According to (Ng, Gani et al. 2007), these end-use properties are obtained by controlling the microstructure of formation. Furthermore, the end-use properties of the structured product are influenced by their rheological and interfacial properties, and therefore these properties must be controlled during the product design (Ng, Gani et al. 2007). Consequently, an integrated product-process design approach is necessary to obtain the required physico-chemical properties of the chemical-based consumer product (Hill 2004). The integrated approach represents a departure from the traditional design approach that follows a sequential path, whereby product design formulation precedes process design considerations and may involve a number of trials-and-error (Wibowo and Ng 2002). This sequential approach sometimes yields sub-optimal design solutions. The overall performance of the chemical-based consumer product depends on the properties of the product's ingredients and its structural attributes resulting from the processing inputs (Wibowo and Ng 2002). Furthermore, one can relate the ingredients composition, process operating condition and process design to the material properties and the product microstructure. However, the challenge often lies in objectively quantifying the product performance as a function of the material properties or its structural properties. Several authors have proposed the use of performance indices as a means of quantifying the relationship between the product performance and these properties (Cussler and Moggride 2001; Cussler and Moggridge 2001; Wibowo and Ng 2002; Ng, Gani et al. 2007). The application of rigorous modeling to obtain theoretical predictive models is reserved for instances where the underlying physics behind the relationship is well understood (Wibowo and Ng 2002). However, in many instances concerning the manufacture of chemical-based consumer products, such knowledge base is still quite limited (Wintermantel 1999) and therefore detailed modeling could prove to be unfruitful (Wibowo and Ng 2002). In such instances wherein the physical phenomena are poorly understood, the black box process can be modeled empirically and the model specified for the given experimental range (Wibowo and Ng 2002). Several examples of chemical product design approaches can be found in the literature (Cussler and Moggride 2001; Wibowo and Ng 2001; Wibowo and Ng 2002; Hill 2004; Solvason, Chemmangattuvalappil et al. 2009) that may include empirical modeling of product properties. A slight modification to the product design model proposed by (Cussler and Moggride 2001) is presented in Figure 3.1.

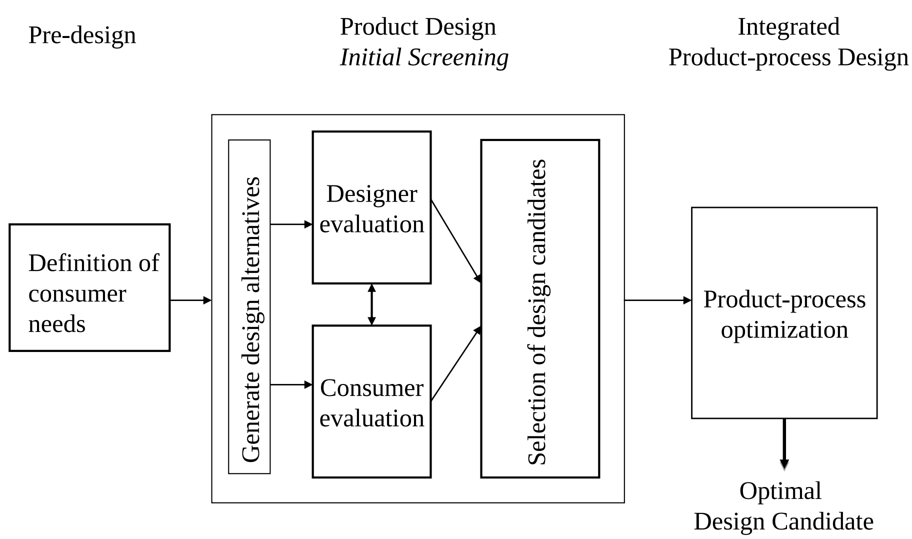



Figure 3.1: Product Design Stages

In general, the stepwise approach involves the capture and translation of consumer needs, the generation of product concepts based on consumer needs, the screening and selection of product candidates and the product manufacture (Cussler and Moggride 2001). However, the design problem formulation must facilitate designer flexibility, in that it allows design adjustments based on specific business or market situations. In the proposed framework market demands, requiring greater consumer involvement, are combined with business and technical design requirements to form two competing design objectives.

## 3.3 Integrated Product Design Framework

The proposed framework offers a comprehensive decision support for selecting an optimal product design. It specifically addresses the unique set of design considerations for the chemical-based consumer products, as outlined in Table 3.1. Furthermore, the framework explicitly incorporates the consumer preference and allows for designer flexibility. The stepwise approach outlined in Figure 3.2 utilizes principles of decision theory, experimental design methods and multi-objective mixed integer optimization techniques.

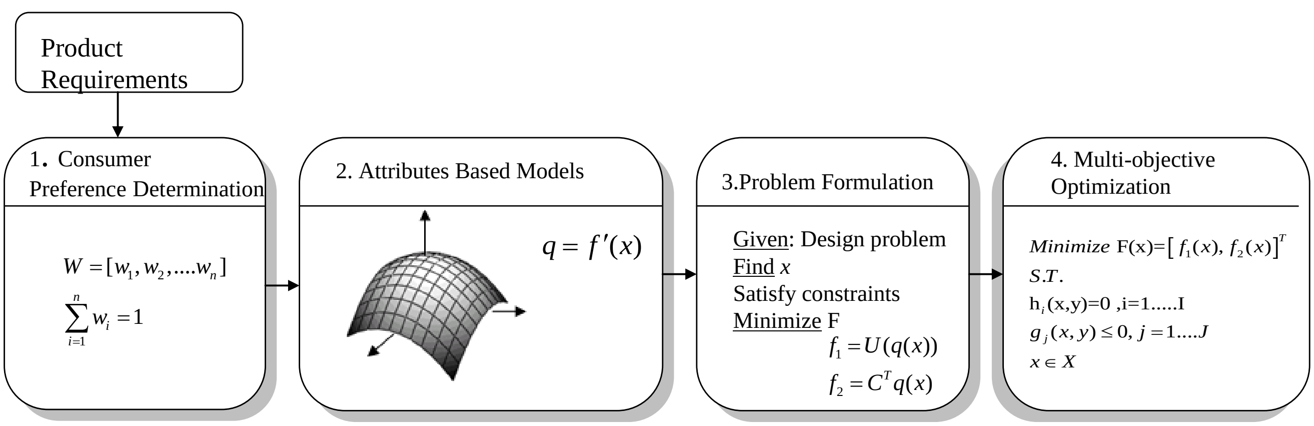



Figure 3.2: Consumer Integrated Product Design (CIPD) Framework

### 3.3.1 Step 1: The Consumer Preference Identification

The design of any consumer-based products requires greater emphasis on end-use product requirements throughout the design cycle (Charpentier and McKenna 2004). These end-use requirements are often identified as functional requirements and quality-based product attributes. Such end-use emphasis warrants an effective mechanism for evaluating consumer preference and subsequently incorporating such evaluation to influence the selection of the optimally designed product. There are many techniques for evaluating and integrating consumer preference found in the literature (Green and Srinivasan 1978; Bouchereau and Rowlands 2000; Forman and Gass 2001; Besharati, Azarm et al. 2002; Yang, Jang et al. 2003; See, Gurnani et al. 2004; Yoon and Kim 2006; Solvason, Chemmangattuvalappil et al. 2009). For example, quality function deployment (QFD) method is commonly used for capturing consumer needs and translating these needs into technical design requirements (Bouchereau and Rowlands 2000). Although widely used, QFD is very time consuming in its application, and according to (Yoon and Kim 2006), it is rather limiting in its ability to determine appropriate customer-oriented technical importance ratings (TIRs). Such limitation can lead to eventual consumer dissatisfaction with QFD-designed products (Yoon and Kim 2006).

In reality, a firm's ability to design and develop successful products depends on its ability to determine the multi-attribute design configuration that maximizes the consumer-based utility, while meeting cost constraints and design specifications. Furthermore, according to (See, Gurnani et al. 2004), some of the common challenges encountered in multi-attribute design space include aggregating of the criteria, rating of the alternatives, assigning weights to individual attributes and modeling the strength of the preferences in attribute. Consequently, a critical component of the design of chemical-based consumer products is the generation and selection of design alternatives that will maximize consumer utility. (Li and Azarm 2000) claimed that there are two main stages in the design selection process: 1) the creation of competing design alternatives and 2) evaluation and selection of the design alternative. Most multi-attribute decision making (MADM) approaches use attributes weights in one form or another to take the decision maker preference into account and to create the utility for the design (Scott and Antonsson 2005). However, one major limitation of explicit weight assignment is the assumption that all attributes are preferentially independent of each other (Sen 2001).

In this study consumer preference is determined by consumer evaluation of individual product samples that represent an aggregate of design attributes. Moreover, by obtaining the overall rating of product samples in a well designed consumer study (Table 3.2), one can determine the influence (or weight) of each attribute from the resulting preference structure.

**Table 3.2: Consumer Study Data Structure**

| | | Performance attributes |
|---|---|---|
| **Product Samples** | **Mean Consumer Rating** | $q_1 \quad \cdots \quad q_n$ |
| $\begin{matrix} d_1 \\ \vdots \\ d_m \end{matrix}$ | $\begin{matrix} p_1 \\ \vdots \\ p_m \end{matrix}$ | $\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix}$ |

As shown in Table 3.2, there is a set of $m$ distinct product samples, $D= [d_1.....d_m]$, each of which is characterized by a unique combination of design attributes in an $n$-dimensional attribute space, $q= [q_1... ...q_n]$. $a_{ij}$ is the normalized or coded value of attribute $j$ associated with product sample $i$ $(i=1......m; j=1....n)$. $p_i$ is the mean of $k$ ratings given by the $k$ randomly selected consumers for the $i^{th}$ product sample. The ratings of the $m$ discrete product samples are carried out by $k$ consumers within a given market segment. By using metric measures to rate the set of product samples, one can perform a multivariate regression to obtain the statistical relationship between the product attributes and the mean score obtained for each product sample.

The coefficient of the derived regression model provides an estimate of the weight $w$ for the individual attribute for this study. Measurement evaluation is followed as a standard procedure embedded in the design framework (Figure 3.2), to address the inherent data reliability concerns associated with the subjective evaluation of the product samples.

3.3.2 Step 2: Attribute-Based Models

Figure 3.3 summarizes a generic model for specifying the competing objectives of the design problem. The model provides the basis for the design and economic evaluation of the single product candidate.

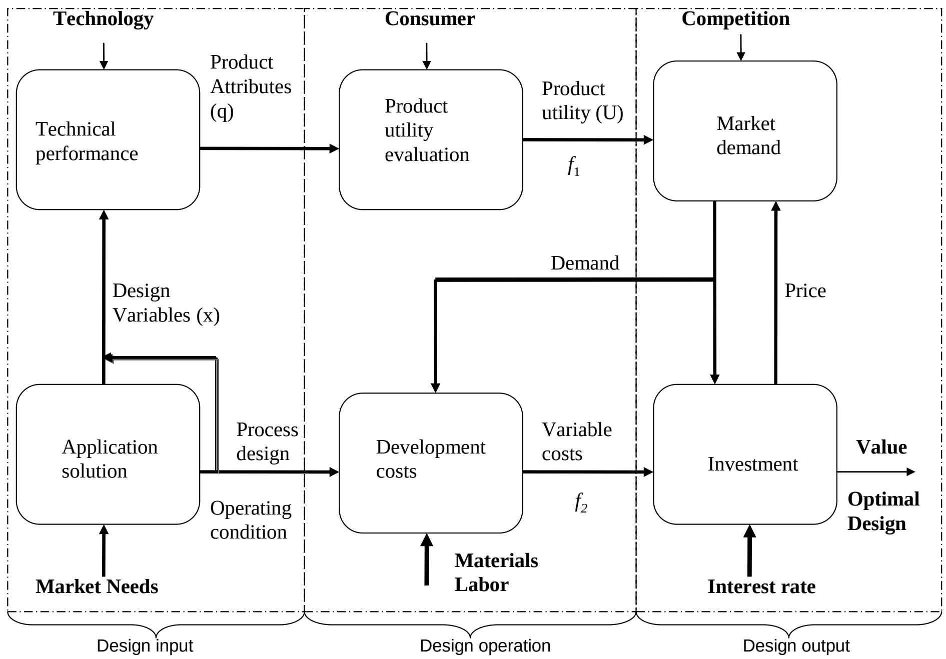



Figure 3.3: Single Product Integrated Design Model (Adapted: (de Weck 2006))

The single product design model shown in Figure 3.3 comprises the design input, the design operation and the design output segments. As depicted in Figure 3.3, the consumer input is integrated throughout all three segments of the design model via the incorporation of market needs and direct consumer evaluation. The activities of the design input segment involve the solicitation of market needs and the translation of these needs into technical requirements by design engineers. Also, within this segment, empirical product-process design models are generated to formalize the relationship between the product attributes (q) and the product design variables (x). Product attributes performance indices identified *a priori* provide a way to quantify the relationship between product attributes (q) and the design variables (x). Product and process requirements, along with attributes performance specifications, help to define the feasible region for the subsequently formulated optimization problem. Solution of the multi-objective optimization problem yields a pareto set of optimal product designs. Using this set, the designer undertakes further trade-off evaluation, compares and ranks the members in order to select the most preferred solution.

### 3.3.3 Step 3: Problem Formulation

The multi-objective problem formulation considers two criteria derived from the single product integrated design model shown in Figure 3.3. The general bi-objective problem is given as:

$$\begin{aligned}
&Min\ F(x) = [f_1(x), f_2(x)]^T \\
&Subject\ to: \\
&h(x) = 0 \\
&g(x) \le 0 \\
&x \in X \subset R^l
\end{aligned} \tag{3.1}$$

Here $[f_1(x), f_2(x)]$ is a vector function of real-valued linear or nonlinear objective functions; $X$ is the set of feasible solutions in the decision space $R^l$; denoting the feasible set of equality constraints, h(x), and inequality constraints g(x) respectively. There exists no solution that simultaneously optimizes both objective functions in problem (3.1). Consequently, the purpose here is to find acceptable trade-offs that yield an efficient solution set instead of a single optimal solution. A feasible solution $x^* \in X$ is said to be efficient if and only if there exist no other feasible solution, $x \in X$ , such that $f_i(x) \le f_i(x^*)$ with at least one $f_i(x) < f_i(x^*)^{i=1,2}$ (Steuer 1996; Arora 2004).

### 3.3.4 Step 4: Multi-Objective Optimization

Various methods are employed to determine the pareto front in a multi-objective optimization (MOO) problem. Most commonly reported are parametric approaches that are based on “weighted scalarization” of the objective functions (Ehrgott and Gandibleux 2002; Sayin and Kouvelis 2005). However, the weighted sum algorithms present a number of limitations, such as its inability to produce unsupported efficient solutions for non-convex objectives as is often encountered in multi-objective integer and mixed integer programming problems (Steuer 1996; Be´rube´, Gendreau et al. 2009). Another common approach used to obtain the pareto front in a multi-objective optimization problem is called the $\varepsilon$ -constraint method. In the $\varepsilon$ -constraint approach, one objective function is optimized using the second objective function as a constraint in the case of the bi-objective problem. The $\varepsilon$ -constraint approach for the bi-objective problem is therefore modeled as follows:

$$\begin{aligned} & Min\ f_1(\mathrm{x}) \\ & \text{Subject to:} \\ & f_2(x) \le \varepsilon_i \\ & h(\mathrm{x})=0 \\ & \mathrm{g(x)} \le 0 \\ & x \in X \end{aligned} \tag{3.2}$$

By parametrically varying the right hand side (RHS) of the constraint ( $\varepsilon_i$ ) given in formulation 3.2, a series of $\varepsilon$ -constraint problems are generated and subsequently solved to yield a set of efficient (or pareto optimal) solutions.

## 3.4 Case Study Illustration

A case study to illustrate the proposed framework was conducted in collaboration with Private Label Cosmetics (PLC) Company, located in Fair Lawn, New Jersey. The company provided the necessary materials and technical support for this study. The consumer integrated product design (CIPD) approach was modeled as a "single level" multi-objective optimization problem in which the consumer utility and the development cost functions formed the two objectives.

### 3.4.1 Product Design Problem Introduction

The primary function of the under eye cream is to reduce periorbital lines and wrinkles by firming the areas of the skin around and under the eye. Three other important product quality attributes identified by the consumer included 1) ease of product application ($q_1$), 2) brightness effect ($q_2$) and 3) smooth feel or smoothness ($q_3$). These sensory product attributes are often characterized using subjective and qualitative evaluation techniques. Consequently, appropriate performance indices were used to obtain a quantitative measure of the product's performance (Wibowo and Ng 2002). Table 3.3 illustrates the required attributes along with their corresponding performance indices.

**Table 3.3: Product Attributes Performance Indices**

| | ***Ease of spread*** *( $q_1$)* | ***Brightness Effect*** *($q_2$)* | **Smooth Feel** **($q_3$)** |
|---|---|---|---|
| ***Performance Index*** | ▪ Application Viscosity, μ<br>▪ Yield Stress, Pa | Colorimetric Value L*a*b* value (L* Brightness) | ▪ Panel Evaluation<br>▪ Droplet Size |
| ***Source*** | Wibowo et al. (2002)(Wibowo and Ng 2002) Herh et al. (1998)(Herh, Tkachuk et al. 1998) | | Wibowo et al. (2002)(Wibowo and Ng 2002) Bernardo et al. (2005)(Bernardo and Saraiva 2005) |

The base cream formulation containing the active ingredient, along with other inactive excipients, remained fixed, while concentrations of three independent ingredients; mineral oil ($x_1$), titanium dioxide ($x_2$) and deionized water ($x_3$), were optimized during this study. The product attributes were formally modeled as a function of the three ingredients and mixing speed ($x_4$). The optimal solutions identify the optimal design alternative and specify the proportions and value of the corresponding design variables.

## 3.4.2 Methodology

### *3.4.2.1 The Consumer Preference – Attributes relative importance*

To assess consumer preference, a market survey was conducted to evaluate eight product design samples. The set of eight product design samples were formulated by product designers to represent a full factorial combination of the product design attributes obtained at two performance levels as shown in Table 3.4. The product samples were evaluated by a panel of five consumer judges with each consumer judge evaluating each sample.

**Table 3.4: Consumer Study Design (coded units)**

| *Product Sample* | $q_1$ | $q_2$ | $q_3$ | **Mean Score, $\mu$** |
|---|---|---|---|---|
| 1 | -1 | -1 | 1 | 3.7 |
| 2 | 1 | 1 | -1 | 7.7 |
| 3 | 1 | -1 | 1 | 6.4 |
| 4 | -1 | 1 | 1 | 7.5 |
| 5 | -1 | -1 | -1 | 2.2 |
| 6 | 1 | -1 | -1 | 5.3 |
| 7 | 1 | 1 | 1 | 9.8 |
| 8 | -1 | 1 | -1 | 7.8 |

Regression analysis was used to obtain the statistical relationship between the consumer mean score and the three product attributes that characterized the product design samples. The coefficient of the multivariate regression provided an estimate of the relative importance of each product attribute. In this study intra-class correlation (ICC) statistical technique was used to assess the reliability of the judges rating. Estimate of the degree of measurement consistency is based on the analysis of variance (ANOVA) (Shrout and Fleiss 1979; McGraw and Wong 1996) results obtained by using Minitab ® statistical software.

### *3.4.2.2. Attribute -Based Models*

A D-optimal designed experiment was generated in the mixture-process space using Design-Expert ® Software package. The triangular layout shown in Figure 3.4 illustrates the location of the points in the mixture space in combination with the process variable levels.

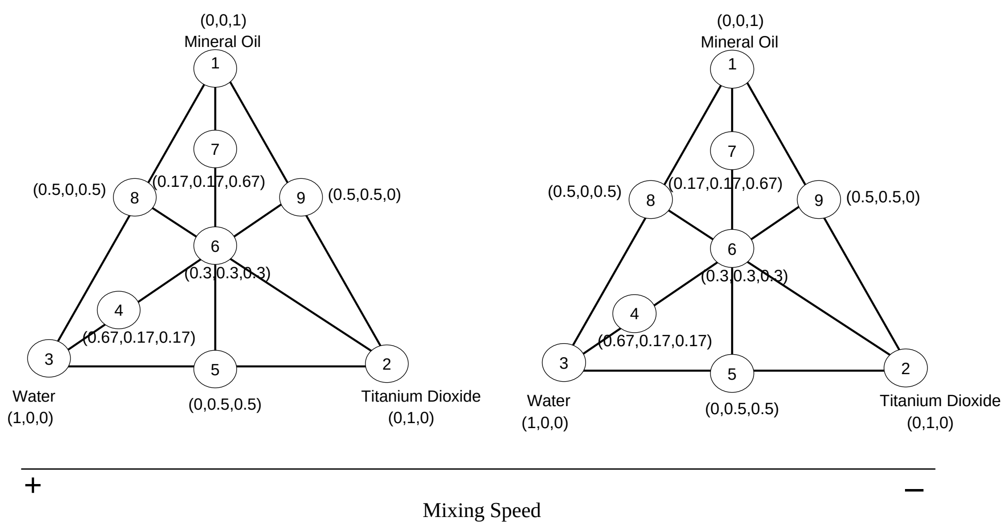



Figure 3.4: Experimental Design Space

Ten additional experimental runs were included to allow for estimates of error. In this study, the mixture space is constrained by the general mixing rule, wherein the sum of all ingredients proportion is restricted to sum to one. There are no further restrictions on the ranges of the ingredient components. The apexes illustrated in Figure 3.4 represent pure component blends, while the interior points represent ternary blends consisting proportion of mineral oil, titanium dioxide and deionized water. The centroid point contains equal amounts of all three ingredients. The combined experimental approach results in running all blend points at the process variable levels as indicated in Figure 3.4.

Sample batches of the under eye cream product were prepared using a Dayton mixer (Model # 12851) with an impeller to vessel diameter of 0.58. Samples colorimetric values were obtained using the color mouse device CM2S model fitted with the ColorMouse Trap application software version 1.04, while viscosity measurements were obtained using a Brookfield viscometer (Model LVT). A panel of five randomly selected judges evaluated each treatment for smoothness using a predefined metric scale. Smoothness measurement data was subsequently evaluated for measurement reliability using the intraclass correlation coefficient (ICC) statistical technique for subjective measurements. In this study we assume that the response can be adequately described by a polynomial in $x_i$. Data obtained from the sensory and analytic measurements are used to calculate Scheffe's (1958)(Scheffe 1958)canonical polynomial for the mixture components. The first order model takes the form:

$$q = \sum_i \beta_i x_i \tag{3.3}$$

While the second order model takes the general form:

$$q = \sum_i \beta_i x_i + \sum_{i<j} \sum \beta_{ij} x_i x_j \tag{3.4}$$

Where $\boldsymbol{q}$ is the dependent product attribute variable, $\beta_s$ are parameter estimates for each main effect and interaction term for the prediction model.

*3.4.2.3 Problem Formulation and Optimization*

The generic single product integrated design model (Figure 3.3) provides a base for the design problem formulation. Furthermore, the appropriate formulation for the consumer integrated product design problem is referred to as a mixed 0-1 bi-objective problem that belongs to the class of multi-objective combinatorial optimization (MOCO) problems. In this formulation, the consumer influence is represented explicitly via the utility objective function. The utility for the $i^{th}$ design alternative is expressed as:

$$U(i) = \sum_{j=1}^{3} w_j \, \tilde{q}_{ji} \tag{3.5}$$

where $w_j$ is the normalized weight of the $j^{\text{th}}$ attribute based on consumer rating; $\tilde{q}_{ji}$ is the normalized value of the $j^{\text{th}}$ attribute for design alternative $i$ and is defined as:

$$\tilde{q}_{ji} = \frac{q_{ji} - q_{jo}}{q_j^{\max} - q_{jo}} \tag{3.6}$$

where the values of $q_j^{\max}$ and $q_{jo}$ are the threshold and reference values for attribute $j$ respectively. The bi-objective optimization for the chemical-based consumer mixture problem can be represented as:

$$\begin{aligned}
&Max\ f_1 = f_1(\tilde{q}(x), y, w) \\
&\text{Min } f_2 = f_2(q(x), y, \text{x}) \\
&S.T. \\
&\text{h}_i(\text{x,y})=0, \text{i}=1.....\text{I} \\
&g_j(x, y) \le 0,\ j = 1....J \\
&Ax \le b \\
&x \in X \\
&y \in (0,1)
\end{aligned} \tag{3.7}$$

Problem (3.7) corresponds to a mixed-integer linear or nonlinear problem with mixed-integer (in)equality constraints. Here in this formulation $x = [x_1, x_2, \cdots x_l]$ is the vector of design variables, $f_1$ is the consumer utility function, $f_2$ is the cost function associated with the selected product attributes (ingredients, labor and process operating variables cost) and process design variables, ***y*** is the vector of binary integer variables indicating the existence of a product attribute or the existence of an attribute above a predefined value, such that :

$$y_j = \begin{cases} 1 \text{ if } \text{q}_j > q_{jo} \\ 0 \text{ if } \text{q}_j \le q_{jo} \end{cases} \tag{3.8}$$

where *w* is a vector of attribute weights such that $\sum_{j=1}^{n} w_j = 1$ and $w > 0$; $\text{h}_i(\text{x,y})=($ is the $i^{th}$ equality constraints representing either the mixing rules for product properties, the process models or process design specifications, $g_j(x, y) \le 0$ is the $j^{th}$ inequality constraints related to the product performance specification and/or environmental constraint and $Ax \le b$ refers to the product economic constraints. In problem (3.7), the integer variables represent the differentiating characteristics (or structural characteristics) of the product which is defined by the product's unique set of attributes. Conversely, the continuous variables determined the product's operating characteristics as defined by the corresponding attributes levels (Mavrotas and Diakoulaki 2005).

In this study we employed the $\varepsilon-$constraint method for producing efficient solutions in the bi-objective optimization problem, and adapted the strategy for exact solution of multi-objective combinatorial optimization (MOCO) problems proposed by Be´rube´ et al. (2009) (Be´rube´, Gendreau et al. 2009). In the scheme proposed by (Be´rube´, Gendreau et al. 2009), a sequence of $\varepsilon-$constraint problems was generated based on a progressive reduction of $\varepsilon_i$, which then utilize a branch and cut procedure to solve the inner problem for reducing values of $\varepsilon_i$. An alternate solution approach employed the branch and bound algorithm that was developed by (Mavrotas and Diakoulaki 2005) to find all the efficient points of the bi-objective problem for a reduced linear attribute model or first order attribute model problem. The modified branch and bound algorithm deviates from conventional B&B approach by performing two optimizations for the bi-objective problems at each node (Mavrotas and Diakoulaki 2005). The execution of this procedure encounters specific challenge related to the partitioning of the bi-objective problem (3.7). However, such challenge is addressed in details in the work undertaken by (Mavrotas and Diakoulaki 2005)

From the generated set of efficient solutions the product designer ranked the alternatives to select the most preferred efficient design alternative based on further evaluation.

*3.4.2.4 Evaluation of the Product Design Alternative*

Physiochemical properties evaluation provided a more scientific basis for characterizing the under eye cream product. As noted by (Pena, Lee et al. 1994), the rheological properties of a cream are determined by "the structure formed by its ingredients". Furthermore, rheological behavior is directly related to a wide range of quality attributes such as ease of application, skin feel and product stability (Miller and Löffler 2006). In this study, the flow and deformation behavior of the designed product was evaluated and compared to that of a commercially available product. A Bohlin Gemini HR nano rheometer (Malvern Instruments), fitted with a 20mm parallel plate geometry system, was used to determine the viscoelastic behavior of the study materials. Oscillatory experiments were performed to evaluate the under eye cream viscoelastic properties. Measurements of the storage (elastic) modulus $G'$ and loss (viscous) modulus $G''$ were also obtained and compared.

## 3.5 Results & Discussion

The regression coefficients of the performance attributes obtained from the consumer study are displayed in Table 3.5 along with the assigned attributes weights.

**Table 3.5: Estimated Coefficients and Weights for Mean Consumer Score (coded units)**

| ***Performance Attributes*** ($q_j$) | ***Regression Coefficients*** ( $c_j$) | ***Normalized Weights***( $w_j$) $w_j = \frac{c_j}{\sum_j c_j}$ |
|---|---|---|
| Ease of application ($q_1$) | 1.02 | 0.3 |
| Brightness Effect ($q_2$) | 1.92 | 0.5 |
| Smooth Feel ($q_3$) | 0.57 | 0.2 |

Reliability evaluation of the subjective consumer ratings yielded intra-class correlation coefficient (ICC) values of 0.7 for the individual rating and 0.92 for the averaged rating. These ICC values satisfy the generally agreed upon limit for satisfactory reliability coefficient(Shrout and Fleiss 1979; McGraw and Wong 1996; Pellis, Franssen-van Hal et al. 2003) (Futrell 1995)and indicate sufficient consistency among the judges rating for any given product sample. Statistical models obtained from the mixture design study (Figure 3.4) define the utility and cost functions in the multi-objective formulation given in (3.7).

The normally distributed attribute performance responses were fitted to canonical mixture models via least square regression and evaluated for their goodness of fit. The reduced attributes models obtained for the specific experimentation range are summarized in Table 3.6:

**Table 3.6: Empirical Attribute Models**

| ***Performance Index*** | ***Statistical Relationship*** | **R-Sq. (Adj.)** |
|---|---|---|
| Ease of application ( $q_1$) - Application Viscosity | $= 1.39x_1 - 1.68x_2 + 0.38x_3 + 0.9x_1x_4$ | 92.5% |
| Brightness effect ($q_2$) - L*a*b* value | $= 55.75x_1 + 74.5x_2 + 54.5x_3$ | 94.7% |
| Smooth Feel ( $q_3$) - Panel evaluation score | $= 9.2x_1 - 4.06x_2 + 7.8x_3 - 4x_1x_2 + 8x_1x_3$ | 94.2% |

The reported attribute models include only significant model terms at the 95% confidence level ($p$-value less that 0.05). Furthermore, the reduced statistical models for the three attribute responses have high adjusted $R^2$ values, as indicated in Table 3.6. Analysis of model residuals proved normality and indicated no model bias over the range of experimental runs. These empirical models are subsequently used to determine the utility and cost objective functions given in the optimization formulation (3.7). Figures 3.5 and 3.6 show the response surface contour plots for the unconstrained brightness and smoothness attributes response. The dependence of each attribute on the blend composition provides input into determining each attribute performance specification.

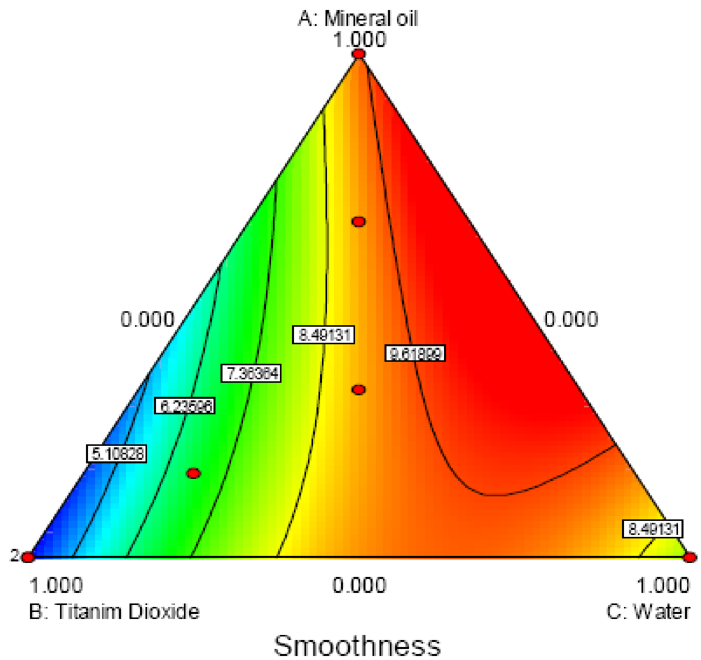



Figure 3.5: Contour Plot of Smoothness Model with Mixing Speed at 60 RPM

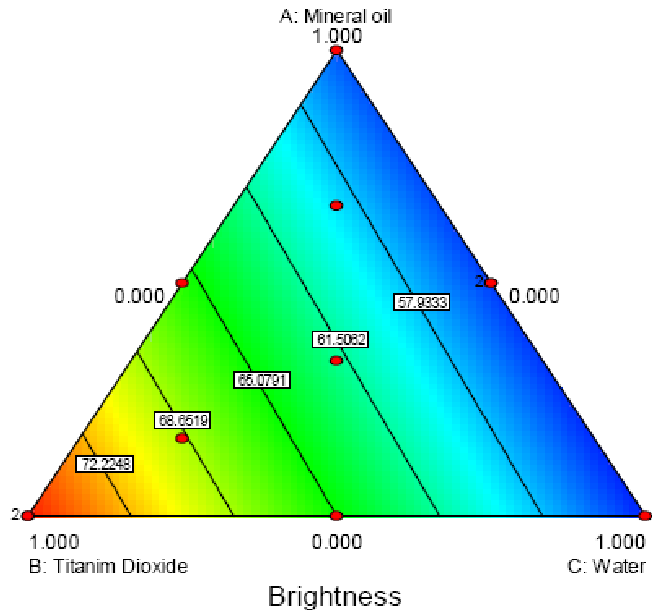



Figure 3.6: Contour Plot of Brightness Model with Mixing Speed at 60 RPM

The set of efficient solutions was obtained using the $\varepsilon$-constraint method as illustrated in Figure 3.7.

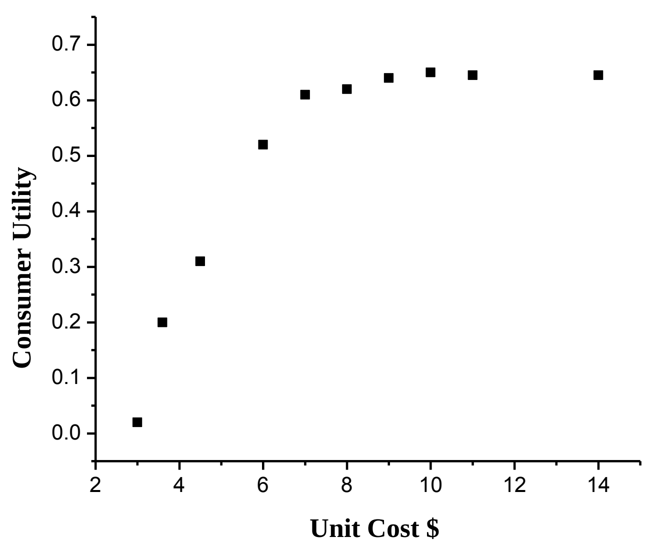



Figure 3.7: Efficient Frontier - Under Eye Cream Formulation

The generation of the design alternatives (set of efficient solutions) is followed by the designer's selection of the "most preferred" design based on critical design tradeoff considerations. The Pareto front shown in Figure (3.7) indicates a gradual increase in the consumer utility with an increase in product investment. Beyond the critical cost of \$7.00 /unit there is no appreciable increase in consumer utility value. Consequently, further investment towards product design beyond this point would yield non-appreciable return and would be considered "wasted" product investment. Such information would be very valuable input to the firm's decision making process. The set of efficient solutions was further ranked based on their normalized cost/utility ratio in order to select the preferred design alternative. The values of the design variables and attribute set of the preferred design is given in Table 3.7.

**Table 3.7: Optimal Mixture Design for Preferred Design Alternative**

| **Optimal Mixture Design** | **Attributes $[y_1,y_2,y_3]$** | **Normalized Cost** | **Utility** | **Normalized Cost/Utility** |
|---|---|---|---|---|
| [0.25, 0.35, 0.4] | [ 1, 1, 1 ] | 0.36 | 0.61 | 0.59 |

The optimal design was obtained at an agitation rate of 60 rpm. As shown in Table 3.7, the normalized cost/utility value of the select design is found to be 0.59, while designs requiring investments beyond the critical \$7.00/unit value gave normalized cost/utility values ranging from 0.75 to 1.64. The higher the normalized cost/utility value the lower the potential return on the design investment. Therefore, a normalized cost/utility ratio greater than 1 indicates a potential economic loss for the firm. Such insight is easily obtained by explicitly integrating the consumer input into the design process for technical and economic design considerations.

Further evaluation of the select design was conducted, for validation, by comparing its rheological properties with similar properties of a (similar) commercially available product. The results of the comparative study are presented in the appendix section.

## 3.6 Conclusions

In this chapter, we present a simple and useful approach that is based on the generic single product integrated model for consumer-based product design shown in Figure 3.3. The consumer integrated product design (CIPD) framework facilitates the generation of efficient product design solutions via a mechanism that explicitly incorporates consumer input and economic criteria. Such explicit incorporation of two competing objectives, in a bi-objective formulation, ensures consumer influence in design tradeoff considerations.

In an effort to accelerate the time-to-market and reduce costs, firms sometimes risk product failure in the marketplace by omitting consumer preference from final design considerations. Furthermore, efficient incorporation of consumer influence helps firms to create product differentiations that are truly valued by the consumer. This valued–add objective is achieved while ensuring viable economic investment towards product design efforts.

The integrated framework specifically considers the unique set of challenges and design requirements associated with chemical-based consumer product (Table 3.1) by incorporating consumer influence, empirical property models and subjective product evaluation. In the case study example, the selected optimally designed under eye cream product exhibited the characteristics of predominant elastic behavior, shear thinning and low yield stress. These factors satisfy the primary requirements for the cosmetic cream product (Förster and Herrington 1998). Moreover, the selected design compares well in performance relative to the commercially available product as shown in Appendix 8.1.

## 3.7 List of Notations

| | |
|---|---|
| $a_{ij}$ | The normalized value of attribute *j* associated with consumer rated sample *i* |
| $\varepsilon_i$ | Right hand side (RHS) parameter of the $i^{th}$ constrained objective function |
| F | Set of objective functions for the multi-objective optimization problem |
| $f_1$ | The general consumer utility function |
| $f_2$ | The development cost function |
| $G'$ | The storage (elastic) modulus |
| $G''$ | The loss (viscous) modulus |
| $g_j(x,y)$ | $j^{th}$ inequality constraint |
| $h_i(x,y)$ | $i^{th}$ equality constraint |
| $I$ | Total number of equality constraint |
| $J$ | Total number of inequality constraints |
| $k$ | Number of consumer respondents |
| $m$ | Total number of product samples for consumer ratings |
| $n$ | Total number of attributes in the product design problem |
| $N_{De}$ | The Deborah number |
| $P_i$ | Mean of *k* ratings for the $i^{th}$ sample |
| $q_j$ | The $j^{th}$ product attribute |
| $q_j^{\max}$ | Threshold value set by product designer for the $j^{th}$ attribute |
| $\tilde{q}_{ji}$ | The normalized value of the $j^{th}$ attribute associated with the $i^{th}$ design alternative |
| $q_{jo}$ | Value of the $j^{th}$ attribute that characterizes the base or reference product |
| $U_i$ | Consumer utility function for the $i^{th}$ design alternative |
| $w_j$ | Weight of the $j^{th}$ attribute |
| $x$ | Vector of product design variables |
| $y$ | Vector of binary ( integer) variables |

# Chapter 4

# MODELING AND OPTIMIZATION OF PRODUCT DESIGN AND PORTFOLIO MANAGEMENT INTERFACE

The chapter presents modeling and analysis of product design and product portfolio management (PD-PM) domains interaction using an integrated simulation-optimization model. To represent the interactions, the product design phase is modeled as a discrete-scenario static system. The goal of this chapter is to develop a decision support framework that relies on product design – product portfolio management integration in order to aid product design planning and design execution. We utilize dependency matrix approach to illustrate domain relation between the product design and product portfolio management domains, and to facilitate their integration. Hence, the process integration model utilizes iterative effects, and their attendant processing duration and costs, to pattern domain interaction. An industrial case study is used to illustrate the application and utility of the proposed approach.

## 4.1 Introduction

The product development process can be characterized by related sets of technological and business decisions that are made *in-situ*. The linking of these two sets of decisions facilitates complete and accurate project (product) valuation by ensuring consideration of both commercial and technical requirements (Georgiopoulos, Jonsson et al. 2005; Michalek, Feinberg et al. 2005). Furthermore, product developers have come to acknowledge that greater coordination and integration of specialized capabilities yield measurable improvement in product development cycle time and development cost (Sogomonian and C.S. 1993; Krishnan 1998; Bode, Schomacker et al. 2007). However, while acknowledging the need for technological and business integration, researchers have also admitted that there is a real challenge in formalizing the relationship between the disciplines (Georgiopoulos, Jonsson et al. 2005; Michalek, Feinberg et al. 2005) and quantifying its impact. According to (Michalek, Feinberg et al. 2005) the reasons for this absence of a coordinated framework can be traced to historical developments and perceptions of disciplinary boundaries. Nevertheless, a number of models have been proposed in the academic literature that seeks to quantify the interdependence of investment decisions and engineering performance decisions via analytical evaluation (Georgiopoulos, Fellini et al. 2002; Georgiopoulos 2003; Georgiopoulos, Jonsson et al. 2005; Michalek, Feinberg et al. 2005). Such models, in forging the linkage of the two disciplines may lead to improved portfolio decisions; however it may not address issues associated with inefficient coordination, therefore yielding less than optimal portfolio decisions.

Recently, (Ng 2004) offered a hierarchical framework that relied on distinctions in decisions length and time scales within a chemical enterprise. Such layered distinction provides the basis for linking business decision making to product and process design; wherein regions of overlap indicate the presence of interaction between levels of decision making. Moreover, the number of iterations between the various levels is minimized when decisions are made in the order of decreasing length and time scales. In recognizing the influence of dynamic market conditions and unpredictable changes in business conditions, this novel approach ignores the random nature of decision making in response to these uncertain conditions. In this study we assess interaction between technical and business domains based on recognized dependence relationship, while accounting for uncertainties that influence interactions.

With a growing intensity in global market competition, firms within the chemical and related industries are forced to develop products at a rapid pace, while minimizing development costs and ensuring product quality (Smith and Ierapepritou 2009). Faced with such stark reality, firms must optimize their development process by eliminating inefficient practices such as wasteful iterations and ineffective communication during the product development process (Clark and Fujimoto 1991; Ulrich and Eppinger 2000; Browning and Eppinger 2002; Cho and Eppinger 2005; Wang and Lin 2009). Such industry imperative warrants the application of a wide range of streamlining strategies; including efficient coordination across disciplinary boundaries. Other practices aimed at reducing product development cycle time include activity crashing, overlapping of activities and concurrent exploration of design alternatives (Graves 1989). A search of the literature revealed a disproportionate focus on product design activities as targets for streamlining the product development process (Steward 1981a; Millson, Raj et al. 1992; Langerak and Hultink 2008; Langerak, Hultink et al. 2008). (Steward 1981a) introduced the problem of managing product design activities by analyzing the flow of information embedded in the design of a given product. In subsequent studies, (Eppinger, Whitney et al. 1994) introduced the design structure matrices (DSM) to enhance the capability for evaluating product design activities.

According to (Roemer and Ahmadi 2004), the management of the development process may require coordination between design activities with complex information dependencies. However, such coordination must extend beyond the product design domain in order to realize maximum efficiency accompanying product development execution. Hence, in this study we have expanded the field for product design coordination beyond intra-design activities and explore opportunities for product development performance improvement by modeling the integration of product design domain and project section aspect of the product portfolio management domain, as shown in Figure 4.1.

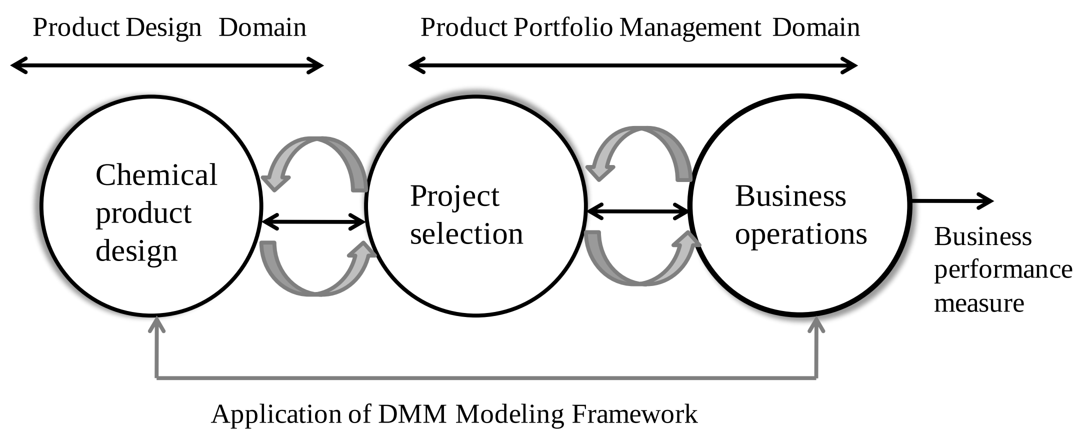



Figure 4.1: Linking Domains Decision Elements

Monte Carlo simulation method was used to accommodate uncertainties via the generation and analysis of discrete random scenarios that characterized the domains interactions. The scenarios were used to model states of iterative effects between the product design and the product portfolio management domains. In the proposed computational framework, the output of the simulation model is directed to the optimization module to yield the optimal scenario and corresponding design decision variables. The simulation optimization problem for the stochastic system can be defined as:

$$\underset{y \in Y}{Min}\, F(y,\omega) \equiv E\left[Z(y,\omega)\right] \tag{4.1}$$

where $F(y,\omega)$ is the expected performance obtained from the simulated output, $Y$ defines the feasible region; $E$ is the expectation operator; y is the system's decision vector, $\omega$ is the random vector defined on a select probability space; while $Z(y,\omega)$ is a random vector that represents the simulation outcome. According to (Fu 2002) , the constraint set $Y$ may be given explicitly or it may be implicitly defined. In general, objective functions of the form given in Equation (4.1) for simulation optimization problems must be estimated by taking an average of the observed simulation output over **S** independent and identically distributed (i.i.d) simulated observations, $\omega^1,\omega^2,\ldots,\omega^s$ (Fu 2002). Hence, the approximate optimization problem is given as:

$$\underset{y\in Y}{Min}\,\hat{F}(y,\omega)\cong\frac{1}{S}\sum_{s=1}^{S}Z(y,\omega^s) \tag{4.2}$$

The chapter is organized as follows: In the next section we review the approach for product design – product portfolio management integration. Section 4.3 outlines the domain dependencies that formed the basis of our integrative approach and has contributed to the development of the proposed computational framework. The problem description and model formulation is presented in section 4.4, followed by an industrial case study to illustrate the proposed framework in section 4.5, and concluding remarks in section 4.6.

## 4.2 Product Design-Product Portfolio Management (PD-PM) Integration

Process modeling, simulation and optimization techniques have been widely deployed to address product development performance concerns, such as the pressing need for cycle time reduction (Schmidt and Grossmann 1996; Schmidt, Grossmann et al. 1998;

Subramanian, Pekny et al. 2000; Varma, Pekny et al. 2008). (Schmidt and Grossmann 1996; Schmidt, Grossmann et al. 1998) are recognized as early contributors who have formalized the optimization of new product development process using mixed integer programming.

However, according to (Wynn, Eckert et al. 2007), the modeling of product development process offers unique challenges due in part to the uncertainty that characterizes the design process – a critical stage within product development. Among the factors contributing to the difficulty encountered in modeling product design process, (Wang and Lin 2009) cited the dependence of the process outcome on "the technical decisions that are made by examining the design *in-situ*. Furthermore, in contrasting manufacturing process to product development, they assert that the product development process is one of creativity and discovery and therefore lends itself to trial and error. The creativity is further warranted by uncertainties due to technological risks (Varma, Pekny et al. 2008) shifting customer requirements and changing business conditions. In part, such factors account for the iterative nature of the product development process evidenced by design tasks rework and repeated resource allocation. According to (Chen and Lin 2003) difficulties encountered in designing complex products does not simply arise from their engineering complexity , but also stem from the organizational sophistication necessary to manage the design process. Hence, this study examines the interaction between aspects of product design and product portfolio management process with an aim to resolve some of these difficulties created by wastes and inefficiency.

4.2.1 Product Design and Portfolio Decisions

The term product design refers to the detailed development that yields specification of design variables and parameters. Hence, the goal of the product design process is to create a detailed recipe for producing a product that will satisfy manufacturing, customer and business requirements. Consequently, meeting this goal necessitates active cross-functional participation in order to ensure stakeholders satisfaction and optimal investment decision. For example, (Schmidt, Grossmann et al. 1998) noted that during the development of an agrochemical product, field trials outcome and toxicology profile information were combined with market assessment in making decision concerning future investment. Moreover, management investment decision relies on information from other products within the product development pipeline and other market data (Schmidt, Grossmann et al. 1998).

According to (Smith and Eppinger 1997) the absence of a proper decision strategy for cross–functional teams can lead to poor design and /or unnecessary iterations. Furthermore, many firms undertake product development efforts with unclear and undeveloped strategies for choosing and managing projects (Jalonen 2007). Such actions often lead to ill use of the firm’s resources, unnecessarily long development lead times, pipeline projects that are not aligned to the firm’s strategy and ultimately to the project failure. Product portfolio management involves active decision-making aimed at creating a product mix that returns maximum value for the firm (Georgiopoulos, Fellini et al. 2002). These product development firms face the critical decisions involving the selection of an optimal mix of products aimed at yielding maximum shareholder value over time. According to (Cooper, Edgett et al. 1997) the new product development portfolio management is likely the most challenging decision making problem in modern business. The challenge in portfolio management lies in the fact that it relies on uncertain and unreliable information and operates in a dynamic environment wherein the project outlook is continuously changing. As noted by (Jiao and Zhang 2005) the product portfolio planning problem has largely concerned the marketing community and therefore has been commonly addressed from a marketing perspective. Nonetheless, product portfolio decisions have implications for engineering operations that concerns cost and complexity of interactions among products within the portfolio. Research and development (R&D) management decision making level takes the form of strategic optimal portfolio selection and tactical project evaluation and resource allocation. The introduction of the Stage-Gate process (Cooper, Edgett et al. 1997) facilitates tactical ongoing project review at pre-determined decision points (gates) within the process. In general the project review may involve assessment of details concerning technical and manufacturing feasibility, as well as commercial feasibility in light of budgetary constraints. When approved, the design team is expected to pursue development such as product and process synthesis, product and process modeling and simulation, cost estimation and business feasibility assessment. In addition to these gate reviews, portfolio reviews are conducted on the entire portfolio of projects. Portfolio reviews and decision are also influenced by uncertainties caused by variability in macro-economic conditions, changing competitive landscape and changing business conditions. Hence, portfolio management decision making is characterized by embedded flexibilities (Varma, Pekny et al. 2008) that lead to increased iterations in information flow with its attendant information processing time and costs.

The process requirement for ongoing work and resource assignments, as a key management function within the product development process, warrants the understanding of interdependencies within and between domains by both engineers and business managers (Danilovic and Browning 2007). Figure 4.2 summarizes the aspects of product design and product portfolio domain integration with their respective noise sources.

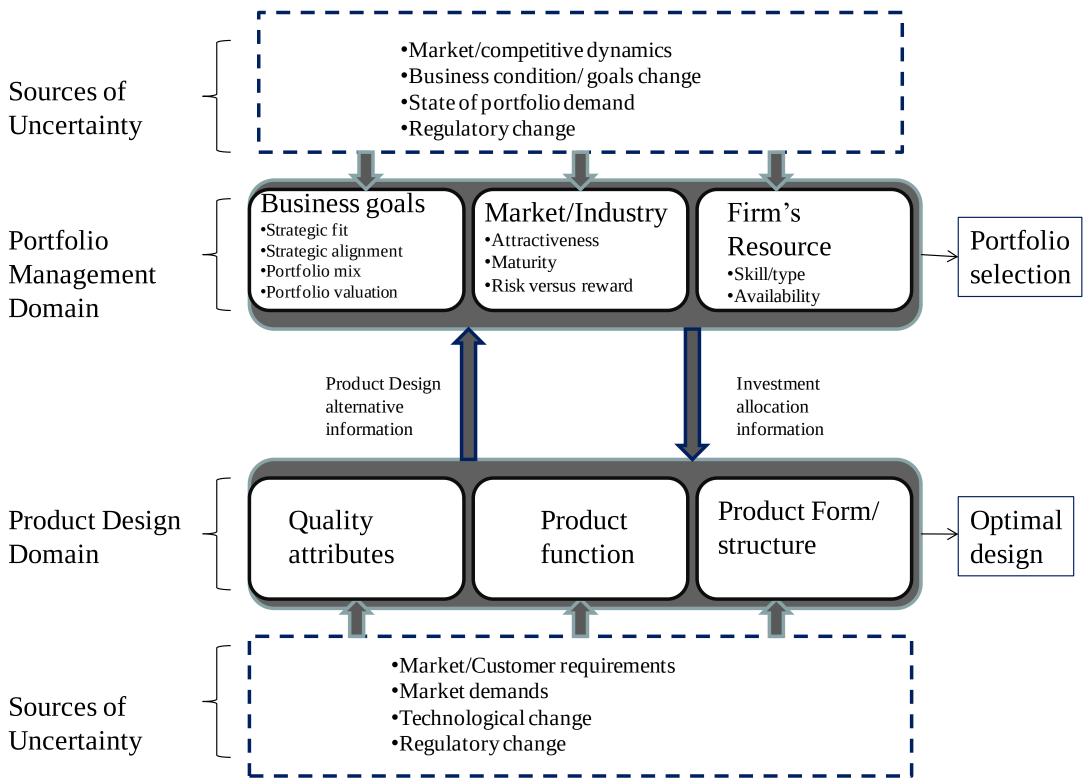



Figure 4.2: Integration of Product Design –Product Portfolio Management Domains

## 4.3 Underlying Dependencies Within the Modeling Framework

The scope and focus of the product design efforts, for a given product, are influenced by product portfolio management level decisions. Resource allocation decisions made at the product portfolio management level are also influenced by technical product design requirements decisions. Hence, decision dependencies characterize the relationship between the product design and product portfolio management domains. In this study we formalize an approach for product design – product portfolio management (PD-PM) integration by utilizing a rectangular domain mapping matrix (DMM) developed by (Danilovic and Browning 2007). The DMM offers a modeling framework that allows us to elicit and capture the underlying relationship between the two domains, and further facilitates analysis of the domains interactions and interdependencies. The DMM consists of row and columns representing the elements of product design and product portfolio management decisions, respectively. Such matrix facilitates the examination of interaction across the extent of both domains. The use of the DMM in this manner creates situational visibility, thus improving coordination and information transfer between the product design and product portfolio management domains. The DMM is contrasted with the design structure matrix (DSM), in that, the DSM finds limited application in self-mapping relationships among the elements of a system in a single domain (Chen, Ling et al. 2003).

Other common modeling frameworks, such as quality function deployment (QFD) and engineering system matrix (ESM), developed by (Bartolomei 2007), are used to model and represent complex systems in product development. QFD matrix is used as an integrative scheme for translating customer requirements into technical design requirements (Bode, Schomacker et al. 2007). More specifically, such domain mapping matrices have found wide application in project planning and analysis work (Chen, Ling et al. 2003; Bartolomei 2007; Danilovic and Browning 2007).

For purposes of illustration, the interaction pattern between the product portfolio management and product design domains is represented by a directed graph and a corresponding mapping matrix as shown in Figures 4.3 and 4.4, respectively.

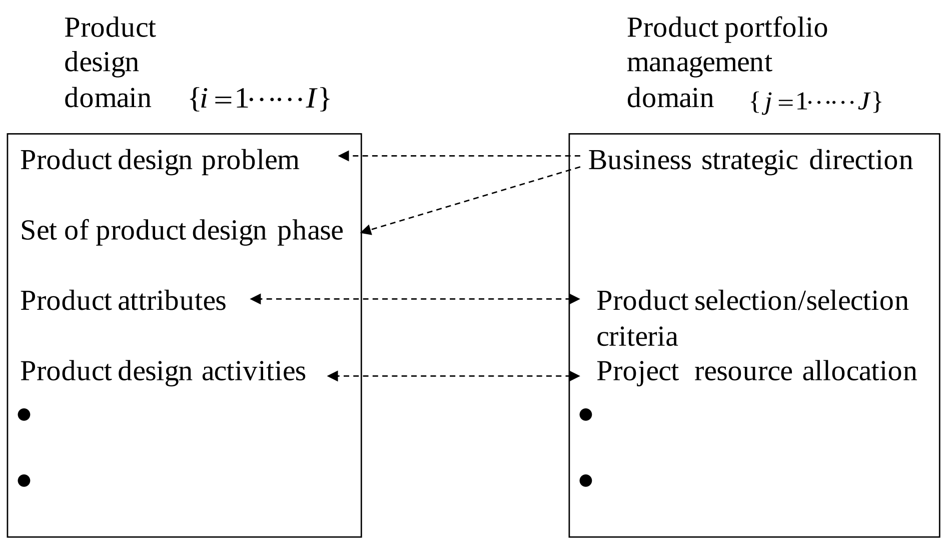



Figure 4.3: Digraph for Product Portfolio and Product Design Interaction

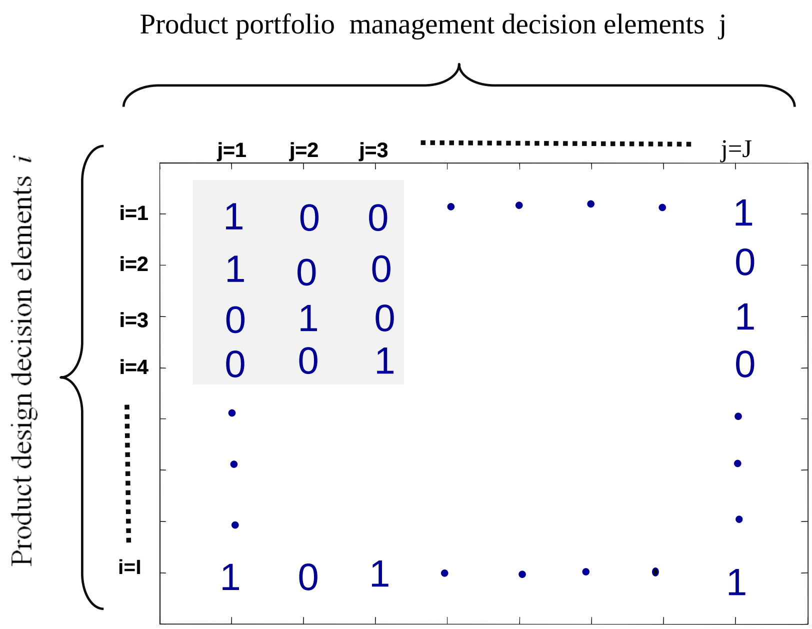
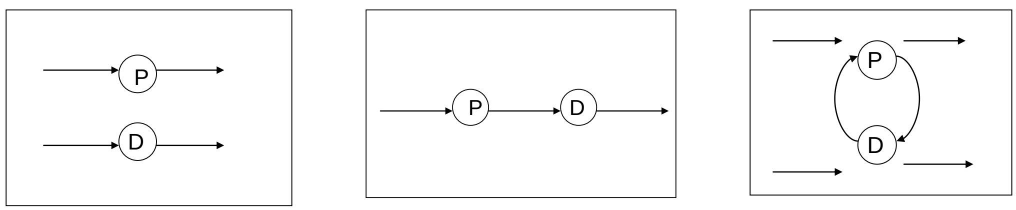



Figure 4.4: Domain Mapping Matrix (DMM) for a Given Project

Major categories of decision making associated with the product design and portfolio management domains are linked as indicated in Figure 4.3. The directed arrows in Figure 4.3 depict information flow between the two domains. In Figure 4.4 a domain mapping matrix (DMM) is used to represent existing dependencies between the two domains. To evaluate this dependency we assign a {0, 1} value to each ordered pairs of domain elements (*i, j*), where *i* is associated with a product and *j* with a product portfolio. Hence, each non-empty cell indicates domains interaction and the potential of iterative flow and iterative processing of information. Therefore, from a project planning and management perspective, each non-empty cell represents time and cost to process information and to perform specific tasks as warranted by the associated decision (business or technical decision). Furthermore, the modification or repetition of such decisions and subsequent actions results in additional consumption of time and resources.

The set of product design and portfolio management decisions can be further classified as, independent, dependent and interdependent decisions to indicate the type and level of domain interactions for any given project within the product portfolio. These dependence structures are displayed in Figure 4.5, where P refers to the product portfolio domain and D refers to the product design domain.




(a) (b) (c)

Figure 4.5: Topographies of Dependence Structures: (a) Independent (b) Dependent(c) Interdependent

Although independent decisions are not influenced by decisions taken in the alternate domain, both the dependent and interdependent decisions influence decisions and activities performed by the other domain and are themselves influenced by such decisions and activities. In this study, DMM is also used as the basis for formulating resource utilization policies to mitigate against unnecessary iterations between the domains. For example, the clustering of dependent and interdependent decisions, as shown in Figure 4.6, enables the development of unique strategies aimed at streamlining the flow of information in order to minimize the number of iterations. Preliminary analysis yielding a

Pareto of the sum of portfolio decision elements and the sum of product design decision elements provide insight to the decision makers regarding the dominant interaction; thus enabling the assignment of mandatory requirements and prioritization of design efforts. Further processing of the DMM can be done to incorporate lean principles and approaches for identifying waste opportunities associated with the flow of information between the product design and portfolio management domains.

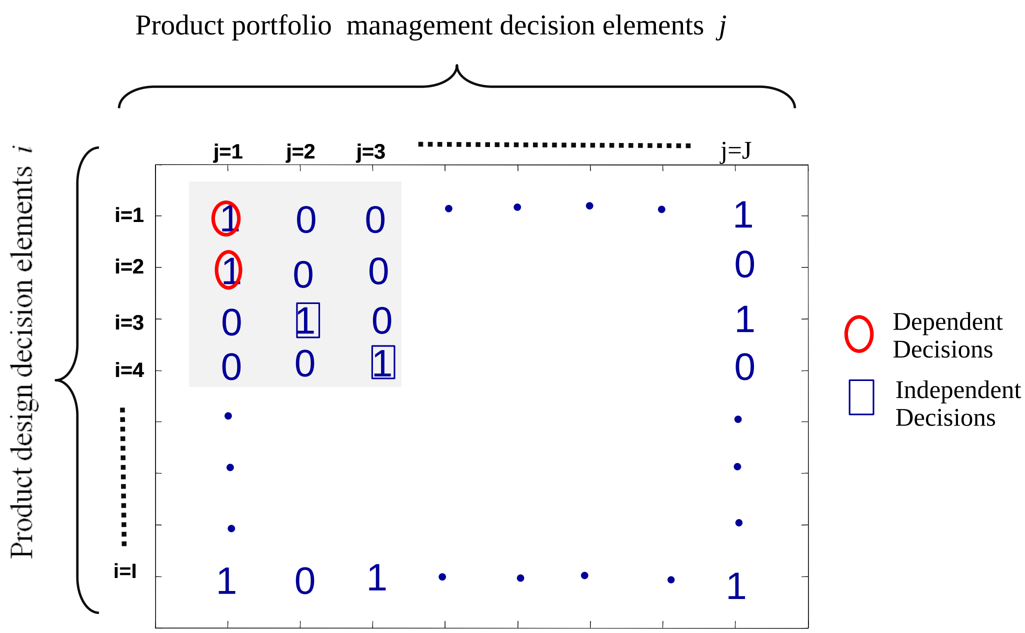



Figure 4.6: Domain Mapping Matrix (classified) for a Given Project

By understanding the impact of the decisions concerning changes in business strategy on product design decision making, for example, the system ensures early and clear communication to the technical community to avoid misalignment of technical efforts and costly rework. Furthermore, the total time duration of the product design phase is directly related to the nature and level of interaction between the product design and portfolio management domains. Given the decision dependence relationship between the two domains, the principal question now becomes how to obtain optimal interaction in an effort to avoid unnecessary project delays and cost while ensuring realistic resource allocations. Our goal in this study is to minimize the number of iterations between the domains by applying relevant streamlining policies and determining the optimal scenario for domains integration for a given set of projects that constitutes the design phase product portfolio.

The following notations and formulations are used to characterize the relationship between decision elements of the product design domain *i* and portfolio domain *j*:

$y_{ijk}$ = binary variable indicating dependent (interdependent) and iterative relationship between product design decision element *i* and product portfolio decision element *j* associated with project *k.* This variable exist for product and portfolio elements that are linked in the DMM (i.e. $n_{ijk} = 1$).

$\omega_{ijk}$ = number of iterations associated with individual cell element $n_{ijk}$ in the DMM of project *k.*

The total number of iterations for project *k* is modeled as:

$$\begin{aligned} &\lambda_k = \lambda_k(y_{ijk}, \omega_{ijk}) \\ &y_{ijk} \in \{0,1\} \quad \forall i, j, k \\ &\omega_{ijk} \geq 0 \qquad \forall i, j, k \end{aligned} \tag{4.3}$$

The total cost due to the iterations associated with project *k* is given as:

$$
\begin{aligned}
& z_k = z_k(y_{ijk}, \omega_{ijk}, \tau_{ijk}, \gamma_k) \\
& y_{ijk} \in \{0,1\} \ \forall i, j, k \\
& \omega_{ijk}, \tau_{ijk} \geq 0 \ \forall i, j, k
\end{aligned}
\tag{4.4}
$$

where $\tau_{ijk}$ represents the mean time taken to process each iteration in matrix cell $n_{ijk}$ of project k; $\gamma_k$ is the mean resource cost rate for project k that accounts for labor and material costs.

In this work we also view the product design process as composed of a set of managerial decisions and a set of product design decisions that are linked via dependent (interdependent) relationship. Iterations between the product design and product portfolio domains are modeled to represent patterns of interaction brought on by inadequate communication, market and business dynamics, as well as by changes in product design requirements. According to (Wheelwright and Clark 1992) iterations increase project cost and completion time and are a major source of the length and expense of the development process. The authors further went on to stipulate that minimizing the number of iterations is a good approximation for concurrently reducing the development time and cost. In this work, iteration refers to a repeat of the flow of information between domains, repeated decision making efforts and tasks resulting from the decisions made. Hence it is assumed that a significant percentage of the resource cost is attributed to the labor component. Iterative efforts may take the form of any of the following:

- Revision of resource allocation decisions due to portfolio management interaction and complexities
- Rework of technical product design tasks
- Repeated preparation of business case for a given product design project due to revised decisions in response to change in business strategy or market conditions
- Repeated product design project status review resulting from inadequate information for decision making

Iteration between the domains takes place among dependent and interdependent decision structures as indicated in Figure 4.7.

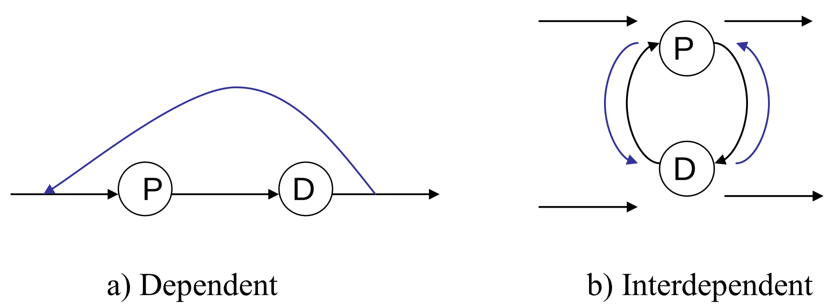



Figure 4.7: Iteration between Product Design and Portfolio Management Domains

We consider that careful product design planning involves accounting for planned iteration that allows for controlled resource allocation and realistic budgeting.

In this work we make a distinction between the design of new products and the redesign of existing products by considering the preliminary data requirements and the necessary precursor steps in the proposed framework. In the case of product re-design we rely mainly on historical performance data. However, in the case of new product design we rely on expert knowledge given the information of project type and the ordered pair of domain elements, (*i, j*), for the given product and product portfolio. In other instances we combine expert knowledge with performance data of similar products, to assess domain dependence relationship and determine initial parameter values.

## 4.4 Simulation/Optimization Model

In product design process execution, the number of any given type of iterations occurring between the product design and product portfolio management domains is uncertain. Hence, $\omega_{ijk}$ shown in Equations 3.4, 4.4 correspond to random variables. Following the work of (Di Domenica, Lucas et al. 2007) we represent uncertainty in the form of discrete scenarios set denoted by $S \equiv \{s \mid s = 1 \cdots\cdots S\}$ for which we estimate the system's performance as indicated by Equation 4.2.

### 4.4.1 System Description

The state of the system is characterized by a static set of product design projects, $\mathrm{A} \equiv a_k \mid \{k = 1 \cdots K\}$, that are present in the product design phase at varying degree of design progress. Associated with each project, $a_k$, is a random network of information flow between the technical product design and the product portfolio management domains; thus enabling discrete decision making concerning resource allocation and product design efforts. Iterative information flow between a set of product design decision elements $i|\{i=1\ldots\ldots I\}$and a set of portfolio management decision elements $j|\{j=1\ldots\ldots J\}$ further characterizes the product design project execution. Hence, for any project $a_k$ there exists a configuration matrix based on the dual domain mapping matrix (DMM) with {0, 1} elements. Associated with each matrix configuration is a set of random number of iterations between the product design and the product portfolio management domains. The action space, for the domains integration in any given state, is a set of intra-phase decisions that consume time and resource upon their execution.

In this study we consider uncertainties by utilizing a discrete-scenario stochastic approach that allows independent estimate of the cost associated with a given scenario. Monte Carlo simulation algorithm is used to generate uncertain scenarios that characterize the product design–product portfolio interactions.

### 4.4.2 Problem Simulation

The simulation model (Equation 4.4) transform the vector of input parameters, specified over the feasible region defined for each project k, into a vector of stochastic output parameters, $\{z_1(y,\omega), z_2(y,\omega), \cdots, z_k(y,\omega)\}$ . We define the product portfolio function $Z(y,\omega)$ as the summation of $z_k(y,\omega)$ that combines the k output variables into one stochastic output performance measure: $Z(y,\omega) = \sum_k z_k(y,\omega)$ . The simulation optimization framework seeks to find optimal settings of the input parameters that optimize the output parameter.

The Monte Carlo method used in this study relied on repeated sampling and statistical analysis to determine the simulated stochastic response and distribution statistics, respectively. The proposed framework relied on the realization that the solution to general simulation optimization problem (4.1) cannot be obtained analytically, and therefore must be estimated via discrete scenario simulation. Such simulation outcome is guided by specific input parameters and assumed probability function. From the product portfolio perspective, a random scenario constitutes a set of product design projects (products), each with a potential number of iterations with associated time duration and cost. Hence, the simulation module provides the distribution of scenarios (random outcomes) for the different realization of the number of iterations along with derived input parameters values. Uncertainties concerning the number of iterations between the product design and product portfolio management domain are modeled with suitable probability distributions in the simulation module. Furthermore, the probability of the scenarios is assumed to be independent. The output from the simulation problem can be described as a unique combination of realization of iteration uncertainties that advances to the optimization module as shown in the integrated model framework (Figure 4.8).

4. 4.3 Simulation /Optimization Framework

This study integrates both simulation and optimization in a computational framework as indicated in Figure 4.8.

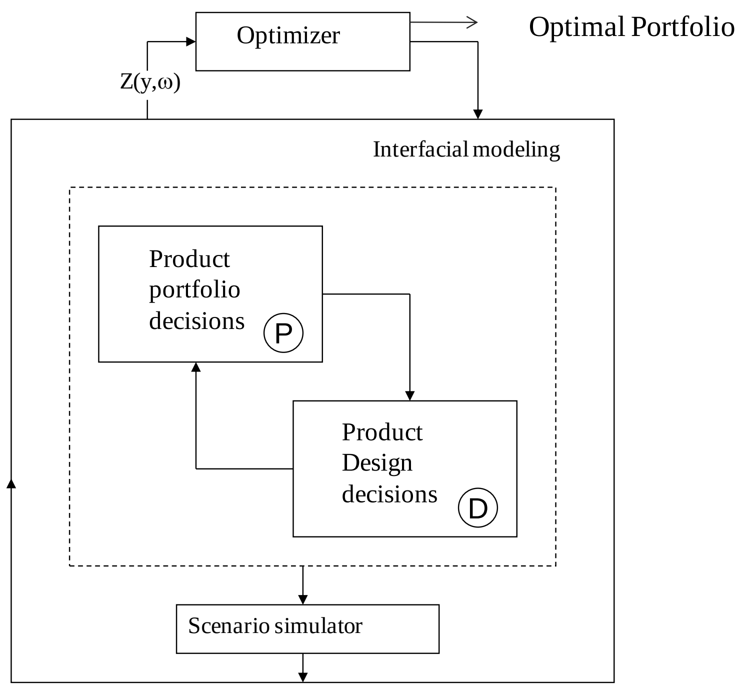



Figure 4.8: Framework for the Integrated Model

The computational framework utilizes Monte Carlo simulation to generate scenarios for the mathematical programming module. The cost based scenario distribution value for iterative effects are used as input parameters to the mathematical programming model. Hence, the general objective of the proposed framework is to identify a scenario that minimizes the objective cost function.

According to (Carson and Maria 1997), simulation optimization provides a structured approach to identifying the optimal output variable values without the need for explicit evaluation of all possibilities. Hence, simulation optimization delivers the dual benefit of resource minimization while utilizing simulation to maximize information about the system (Carson and Maria 1997). These simulation models are used both as objective function and /or constraint function in optimization of complex systems (Azadivar 1999). However, there are unique challenges associated with simulation optimization approaches that mainly relate to the stochastic nature of the objective function and the absence of an exact closed form solution. According to (Fu 2002), the computational burden in solving optimization for simulation problems lies in estimating the objective function whereas in the deterministic case the search of the feasible region accounts for the major computational burden. Furthermore, (Fu 2008) noted that one of the primary challenges in performing simulation optimization involves making the trade-off between the allocations of computational resources for searching the solution space versus conducting additional simulation replications for better estimating the system's performance. The authors further noted that the trade-off consideration takes on even greater significance when the fidelity of the system warrants a computationally expensive simulation. An intractable situation cited by (Fu 2008) involves stochastic simulation that generates millions of random variable, a mathematical programming model with millions of decision variables and an objective function involving a quantity that must be estimated using simulation. These and other challenges are well documented in detailed discussions that compares simulation optimization problems to nonlinear programming problems solution approaches in simulation literature (Azadivar 1999; Swisher, Jacobson et al.

2000; Fu 2002). Common approaches used to solving single objective simulation optimization problems include gradient based search methods, stochastic approximation (SA) method, response surface method (RSM), sample path method and heuristic search methods. While comprehensive reviews of these methods can be found in the literature (Alrefaci and Andradóttir 1995; Azadivar 1999; Swisher, Jacobson et al. 2000; Fu 2002; Fu 2008), we highlight two important requirements for such approaches in addressing the stochastic problem:

1) The approach should be both iterative and integrative: Requiring search and comparison that leads to finding the optimal decision variable value
2) The approach provides an estimation of the optimal value of the objective function

Simulation optimization approaches are developed for single objective optimization applications, multiple-objective applications as well as applications with non-parametric objectives (Carson and Maria 1997). (Artiba and Riane 1998) applied a multi-model system that integrates discrete event simulation, optimization algorithm and heuristics to support production planning and scheduling decision making within the chemical industry. A simulation based optimization framework developed by (Subramanian, Pekny et al. 2000) provided decision support for product portfolio selection and project task scheduling that captures the system's uncertainty via discrete event simulation. In more recent work, (Jung, Blau et al. 2004) applied a gradient based simulation optimization approach in addressing demand uncertainties encountered in the planning and scheduling operations within the chemical process industry.

Increasing development in operation research / computer science interface, resulting from increased computational power, has led to significant growth in commercial implementation of simulation optimization techniques for a wide set of industry applications (April, Glover et al. 2003). Such commercial software offers greater utility for real world situations, and as a consequence more software developers are enhancing the efficiency and program reliability in locating optimal or near optimal solutions (Carson and Maria 1997). One such commercial software is a package called OptQuest® that combines Monte Carlo simulation with intelligent scatter search that utilizes past evaluations. The OptQuest® package also facilitates a mixed integer problem formulation and utilizes neural network procedure as a screening tool(Fu 2002). Such screening capability, along with the incorporation of risk threshold level for objective function evaluation, is highly desirable features of the OptQuest package. Such output analysis techniques facilitate the control of the variance of the stochastic system's response and is considered an advantage offered by such simulation optimization approach (Azadivar 1999).

4.4.4 Stochastic Problem Formulation

Based on the definition of $z(y,\omega)$ given in section 4.2, problem 4.2 can be rewritten as follows:

$$\hat{F}(y,\omega) \cong Min \frac{1}{S} \sum_{s=1}^{S} \left[ \sum_{k} [z_k(y,\omega^s)] \right] \tag{4.5}$$

In this problem formulation we also add the cost of design for each project k by defining:

$$z'_k(x,t) = C_k(x) + \gamma_k t_k \tag{4.6}$$

where: $z'_k(x,t)$ is the basic product design cost function for project $k$ ; $x$ is the product design material decision variable*;* $t_k$ is design time decision variable for project *k*; $C_k(x)$ is material cost function for project *k*. We combine the cost of iterations (Eq4.5) and the basic product design cost (Eq4.6) to yield the following product portfolio cost minimization problem:

$$\begin{aligned}
& Min\left[\frac{1}{S}\sum_{s=1}^{S}\left[\sum_{k}[z_k(y_k,\omega^s)]\right] + \sum_{k} z'_k(x,t_k)\right] \\
& s.t. \\
& g_{rk}(x) \le 0,\ \forall\ r = 1,\ldots,R;\ \ \forall k \\
& h_{mk}(x) = 0, \forall m = 1,\ldots,M;\ \forall k \\
& t_k^L \ \le t_k \le T_k, \forall k \\
& G(z_k, z'_k) \le B_k,\ \forall k \\
& f(y_k)\ \ge 0,\ \forall k \\
& y_k \in \{0,1\},\ y_k \in Y, \forall k \\
& x \in X, t_k \in T
\end{aligned} \tag{4.7}$$

where $y_k$ is the vector of binary decision variable indicating the existence of domain dependence and iteration; $h_{mk}(x)$ and $g_{rk}(x)$ are equality and inequality product design constraints respectively specifying quality and/or materials requirements; R refers to the number of inequality constraints while M refers to the number of equality constraints for the given problem; $G(z_k, z'_k) \le B_k$ is the budgetary constraint for project *k* and $t_k^L \leq t_k \leq T_k$ specifies the product design time constraint for product *k*; the constraint $f(y_k) \geq 0$ indicates planned iteration for the product design project *k* due to dependence relationship. Figure 4.9 summarizes the integrated approach.

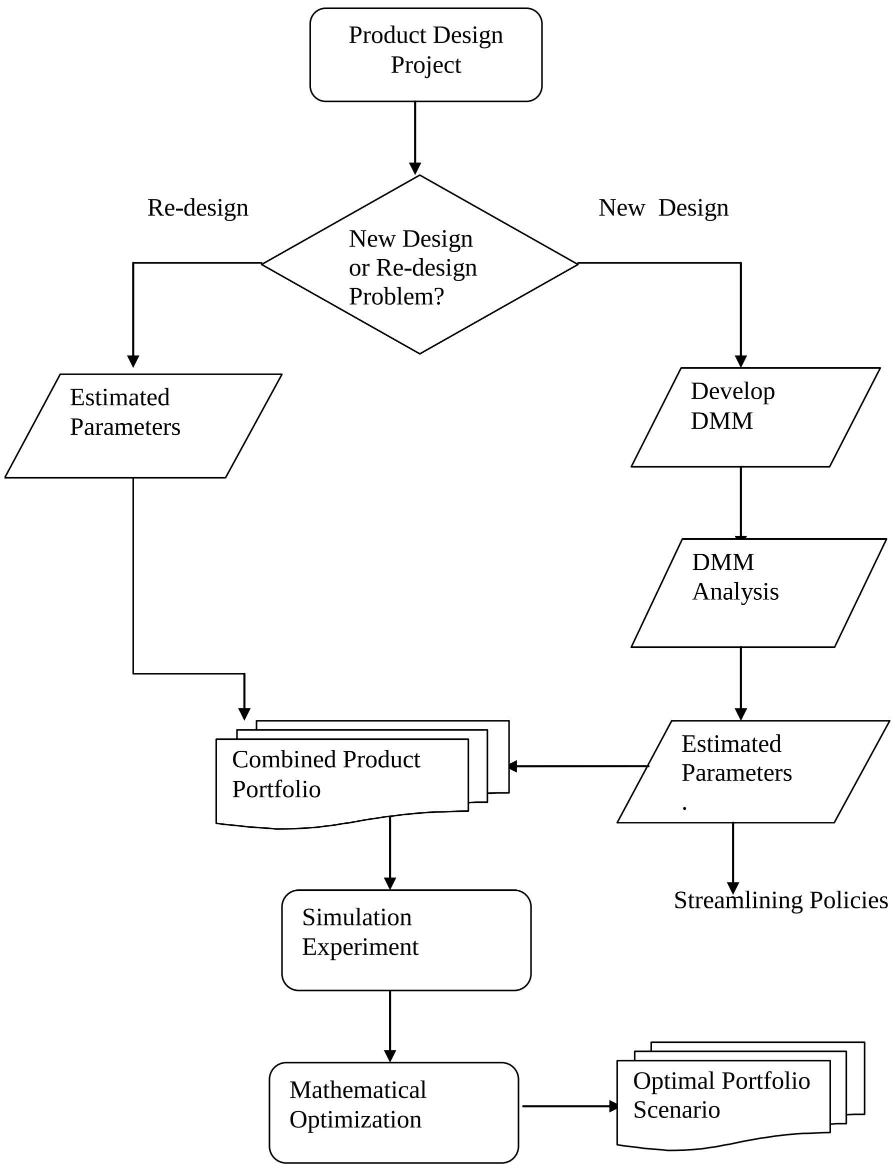



Figure 4.9: PD-PM Integration Methodology Flowchart

## 4.5 Industrial Case Illustration

The implementation described in previous sections is demonstrated via an industrial case based on a personal care product portfolio operation. Product development efforts within the personal care industry is characterized by active communication between the enterprise's management and the research and development (R&D) community, resulting mainly from intense market dynamics due to increasing competition and regulatory changes. Rapidly changing industry trends combined with ongoing market demand for greater product differentiation are dominant drivers for iterative effects encountered during the product design phase. The case study comprises a product portfolio of four product design projects (products) from the same product family as shown in Table 4.1.

**Table 4.1: Personal Care Product Portfolio**

| **Project ($a_k$)** | **Product name** | **Unique product functionality** |
|---|---|---|
| $a_1$ | *Hand and body lotion* | *All skin type moisturizer* |
| $a_2$ | *Elastin collagen cream* | *Moisture restoration* |
| $a_3$ | *Liposome environmental cream* | *Environmental protection* |
| $a_4$ | *Rejuvenating cream* | *Anti-ageing* |

The proposed domain integration approach illustrated in Figure 4.1 has been applied to the case study with an objective to provide decision support to product design planning and execution. A preliminary step in this procedure involves the linking of the product design domain and the product portfolio management domain by utilizing the DMM structure to connect the decision considerations that govern each domain activities.

A set of the product design and product portfolio decision elements for the personal care product line is summarized in Tables 4.2 and 4.3 respectively:

**Table 4.2: Set of Product Design Decision Elements**

| *Design Decision Elements* $\{i = 1, \ldots, 5\}$ | **Description of product design decision elements** |
|---|---|
| $i=1$ | Selection of raw material components to yield desired functional requirements and quality attributes at lowest cost |
| $i=2$ | Selection of the critical quality factors (e.g. Scent, ease of application) |
| $i=3$ | Selection of suitable processing and application technology |
| $i=4$ | Product design alternative selection |
| $i=5$ | Product testing range and method |

**Table 4.3: Set of Product Portfolio Decision Elements**

| *Portfolio Decision Elements* $\{j = 1, \ldots, 4\}$ | **Description of product portfolio decision elements** |
|---|---|
| *j=1* | **Trend**: Strategic shift to natural organic products and green technology |
| *j=2* | **Growth strategy**: Major focus on growth of premium products in the male demographic market segment |
| *j=3* | **Manufacturing operations**: Cost reduction and pipeline productivity goal and measure |
| *j=4* | **Production**: Transition the manufacturing of some products portfolio to offshore production facilities |

The characteristic set of decisions made during the product design process relies on market condition and business direction, in addition to customer requirements. Agreement between these requirements and the product design specifications is a critical project review and product portfolio management decision criterion. Also, we note that business decisions that falls under the categories of industry trend, growth strategy, manufacturing operations and production require a decision response from the technical design community. The DMM presented in Figure 4.10 indicates the dependent (interdependent) relationship between decisions of the product design and product portfolio management domains for the chosen product line.

$$\{j = 1\cdots\cdots4\} \quad \{j = 1\cdots\cdots4\} \quad \{j = 1\cdots\cdots4\} \quad \{j = 1\cdots\cdots4\}$$

$$\{i = 1\cdots\cdots5\} \quad
\begin{array}{c|cccc} & 1 & 2 & 3 & 4 \\ \hline 1 & 1 & 0 & 1 & 1 \\ 2 & 1 & 0 & 0 & 0 \\ 3 & 1 & 0 & 1 & 1 \\ 4 & 1 & 0 & 1 & 0 \\ 5 & 1 & 0 & 0 & 0 \end{array}
\quad
\begin{array}{c|cccc} & 1 & 2 & 3 & 4 \\ \hline 1 & 1 & 1 & 1 & 1 \\ 2 & 1 & 1 & 1 & 0 \\ 3 & 1 & 1 & 1 & 0 \\ 4 & 1 & 1 & 1 & 0 \\ 5 & 1 & 1 & 0 & 0 \end{array}
\quad
\begin{array}{c|cccc} & 1 & 2 & 3 & 4 \\ \hline 1 & 1 & 1 & 1 & 1 \\ 2 & 1 & 1 & 1 & 0 \\ 3 & 1 & 0 & 1 & 1 \\ 4 & 1 & 0 & 1 & 0 \\ 5 & 1 & 1 & 0 & 0 \end{array}
\quad
\begin{array}{c|cccc} & 1 & 2 & 3 & 4 \\ \hline 1 & 1 & 0 & 1 & 1 \\ 2 & 1 & 0 & 1 & 0 \\ 3 & 1 & 0 & 1 & 1 \\ 4 & 1 & 0 & 1 & 0 \\ 5 & 1 & 0 & 1 & 0 \end{array}
\quad \{i = 1\cdots\cdots5\}$$

$$a_1 \quad a_2 \quad a_3 \quad a_4$$

$$\sum_{i,j} n_{ij} = 10 \quad \sum_{i,j} n_{ij} = 15 \quad \sum_{i,j} n_{ij} = 14 \quad \sum_{i,j} n_{ij} = 12$$

Figure 4.10: DMM for the Personal Care Product Line

The domain linkage via DMM ensures early and direct access to information concerning the company's influencing strategies and tactics, thus ensuring strategic alignment while enabling product designers to make important tradeoff decisions that balance the voice of the customer (VOC) with the voice of the business (VOB). For example, in this case study, early knowledge of a strategic emphasis on "natural products" combined with specific focus on cost reduction, has guided the product design efforts in material selection and prioritization of design focus. Hence, the application of the integrated framework reduces the risk of incurring unnecessary iterations and project cancelations that result in wasted sunk cost. A comparison of the DMM for project $a_2$ with that of projects $a_1$, $a_3$ and $a_4$ respectively, indicates a unique influence of the growth strategy on the design considerations of project $a_2$; thus, enabling the design community to make appropriate decision concerning budgeting and resource allocation.

Development and analysis of the DMM led to the establishment of streamlining policies and actions to mitigate against unnecessary iterations between the product design domain and the product portfolio domain. Furthermore, we apply the outcome of the product's DMM ( $\sum_{i,j} n_{ij} > 0$ ) to defining the lower and upper bounds of the random parameter and the decision variable in the subsequent simulation optimization problem.

The simulation- optimization problem concerns the selection of a random optimal project portfolio (scenario) with corresponding decision variables, ***x, y*** and **t** to minimize cost associated with the design of the portfolio of products present within the design phase. Commercially available simulation module (Crystal Ball ®) was used in this study to randomly generate values of the uncertain variables and to guide a set of simulation scenarios to an optimization module. We assume a normal probability distribution function to represent the random variables used in the cost simulation model. Hence, a simulation calculates the model objective by repeatedly selecting values of the random variables from the given distribution.

OptQuest ® software package provided the optimization procedure that uses the output from the simulation model. The optimization module uses an intelligent search procedure to search the feasible space. The package also evaluate the statistical output from the simulation model and compare the statistic of current run with prior run to determine a new set of values for the decision variables . This is an iterative process that improves the objective value over time according to the problem formulation given in Equation 4.8.

$$
\begin{aligned}
& Min\left[\frac{1}{S}\sum_{s=1}^{S}\left[\sum_{k}[z_k(y,\omega^s)]\right]+\sum_{k}C_k(x)+\gamma_k t_k\right] \\
& s.t. \\
& x_{p,k}^L \le x_{p,k} \le x_{p,k}{}^U, \quad \forall p,k \\
& \sum_{p} x_{p,k} = 100, \quad \forall k \\
& t_k^L \le t_k \le T_k, \quad \forall k \\
& z_k(y,\omega^s) + z_k'(t,x) \le B_k, \quad \forall k,s \\
& \sum_{k} y_k \le N \\
& y_k \in (0,1), y_k \in Y, t_k \in T, \quad \forall k \\
& x \in X
\end{aligned}
\tag{4.8}
$$

In this case study the design variables $x$ correspond to the vector of raw material components used in the product formulation. Hence, $x_p$ is the $p^{th}$ raw material component and $\sum_p x_{p,k} = 100$ represents the mixing rule governing each product's material composition; N is the sum total of DMM cell elements, $N = \sum_{i,j,k} n_{ijk}$ , for all projects in the portfolio. The DMM presented in Figure 4.10 illustrates the dependent (interdependent) relationship and therefore the need for deliberate alignment between the product design domain and the product portfolio domain given by $\sum_{i,j} n_{ijk} \ge 0, \forall k$ . Furthermore, the formulation given in (4.8) constrains the number of iterations while restricting iterations to occur between the dependent elements based on the DMM framework.

As indicated in procedure outlined in Figure 4.9, analysis of the DMM has led to the identification of specific resource utilization policies aimed at streamlining the product design planning process. The set of resource utilization policies identified in this case study are summarized in Table 4.4.

| **Table 4.4 : Resource Utilization Policies** |
|---|
| 1. Value-based work requires that product designers give priority to design efforts that align with the business direction as indicated by the DMM |
| 2. Re-use of DMM and knowledge gained for product line extensions projects, product repositioning projects and incremental product improvement efforts |
| 3. DMM outcome provides a basis for assessing work demand versus available capacity |

Further DMM assessment led to recommendations for early integration of raw material suppliers into the product design process for similar products and enhanced bench-scale testing to reduce prototype testing and pilot scale production. Figure 4.11 displays the probability and frequency distribution for the simulated product portfolio cost obtained for the case study.

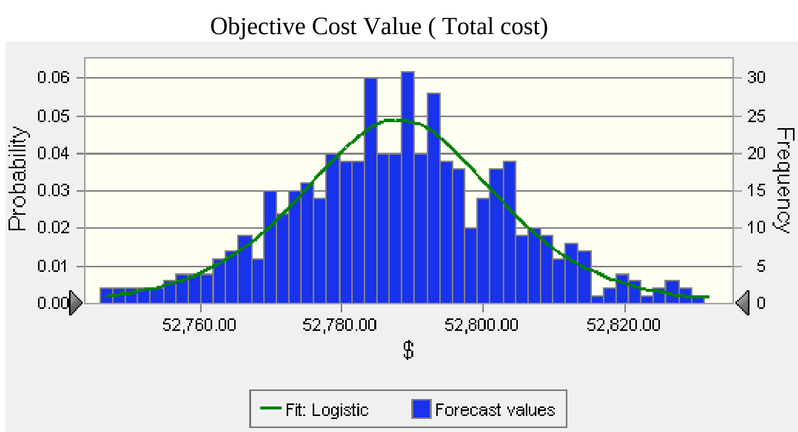



Figure 4.11: The Distribution of Total Product Design Cost Value

The simulation-optimization procedure yielded an optimal mean cost value of $52,788.1 for the portfolio of projects at a 95% confidence level. The cost contributions as displayed and compared in Table 4.5 indicate the mean design cost for each project and the percent of the total cost that is due to iterative effects.

**Table 4. 5: Product Design Cost Estimate**

| **Products** | **Mean Design Cost $** | **Coefficient of variation** | **Iterative Cost $** | **% Iterative Cost** |
|---|---|---|---|---|
| $a_1$ | 8765.68 | 7.821e-04 | 46.57 | 0.5% |
| $a_2$ | 8478.25 | 8.6739e-04 | 74.69 | 0.9% |
| $a_3$ | 14,838.36 | 0.0010 | 127.8 | 0.9% |
| $a_4$ | 19,906.05 | 0.0035 | 552.36 | 2.7% |
| Project Portfolio | 51,988.34 | 3.03e-04 | 799.80 | 1.5% |

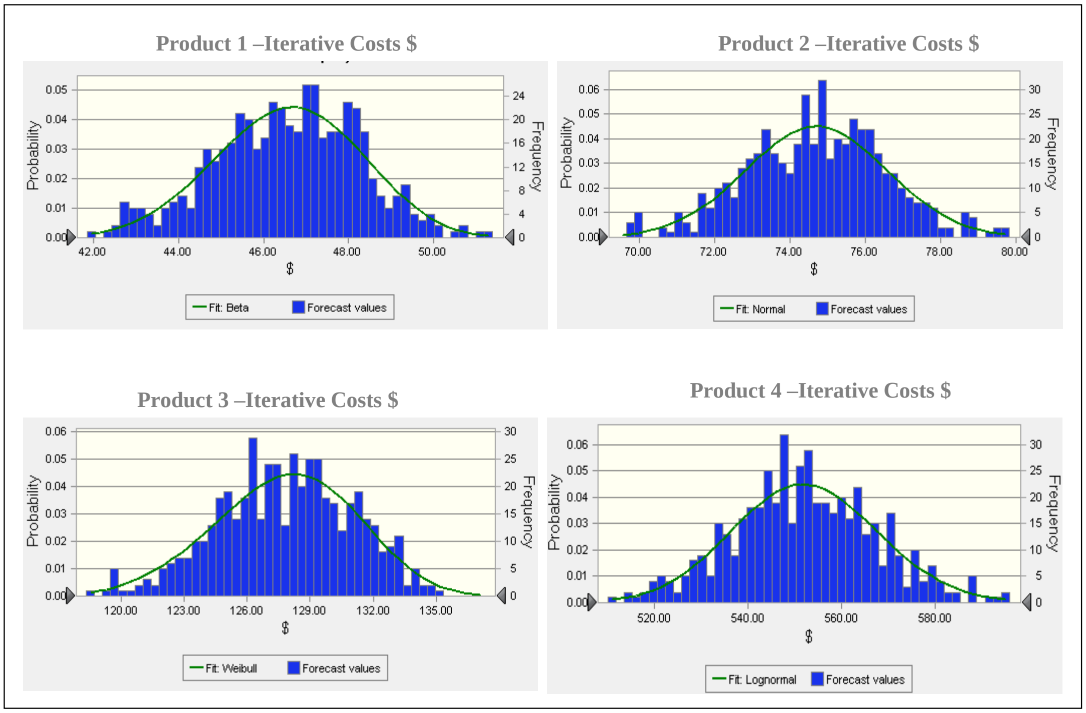



Figure 4.12: Distribution of Product Design Iteration-based Cost Value

As shown in Table 4.5, the isolated iterations cost ranged from 0.5 to 2.78% of the total product design cost for individual projects. As depicted in Table 4.5 product $a_4$ has the highest coefficient of variation and records the greatest percent of iterative cost. This variability results from uncertainty encountered during product design execution as outlined in Figure 4.2. Optimal decision variables values obtained for each product (project) $a_k$ are summarized in Table 4.6.

**Table 4.6: Optimal Product Design Values**

| | Product Design Decision Variables | | | | | |
|---|---|---|---|---|---|---|
| **Projects** | $x_1$ | $x_2$ | $x_3$ | $x_4$ | ***t*** ***( hours)*** | **Number of iterations** $\sum_{ij} y_{ijk}$ |
| $a_1$ | 87.69 | 4.05 | 0.162 | 8.1 | 291.6 | 10 |
| $a_2$ | 69.89 | 4.86 | 5 | 20.25 | 423 | 15 |
| $a_3$ | 64 | 14.13 | 0.81 | 21.06 | 423 | 14 |
| $a_4$ | 72.3 | 4.86 | 5.3 | 17.56 | 567 | 12 |

The optimal design variables obtained from the feasible set are used to satisfy the technical and economical requirements for each product design projects; thus minimizing the risk of project gate reviews rejection and project delays, due to unnecessary trial and error testing and evaluation. In the case study we have found a mean iterative cost of $799.8 which is equal to 1.5% of the mean cost for the studied portfolio of projects. The iterative cost, as a percent of the portfolio budget, serves as an indicator for the implementation of the resource utilization policies identified via the DMM. In this study, an iterative cost representing 1.5% of the portfolio budget falls well within the standard deviation of the portfolio cost value and is considered statistically insignificant. However, over time such cost has practical significance to the business operations and therefore warrants the implementation of the resource utilization policies. Furthermore, by obtaining an estimated mean iteration-based cost value, firms can make more realistic budget allocation towards product design efforts by accounting for hidden iteration-based costs.

## 4.6 Conclusions

In this work we offer a formalized approach to modeling and quantifying the interaction between the product design domain and the product portfolio management domain, with the aim to provide decision support to the product design community.

The application of the proposed procedure secures *a priori* alignment of product portfolio management level considerations to product design activities, and subsequently makes allowance for iterative effects that may accompany such interactions. The combined implementation of product design streamlining policies and processed iterations provides meaningful support to the technical design community by enabling intelligent trade-off decisions making while limiting iterations during design execution. Furthermore, the proposed procedure provides greater control over budget and people resource allocation by establishing early priorities through the alignment of product design decision making to portfolio management level considerations.

## 4.7 List of Notations

$a_k$ = $k^{th}$ product design project

$B_k$ = Product design budget constant for project *k*

$C_k(x)$ = Basic product design cost function for project *k*

D = Product design domain symbol

E = Expectation operator

$F(y,\omega)$ = Expected portfolio performance obtained from the simulated outcome

$\hat{F}(y,\omega)$ = Approximated product portfolio performance measure

$f(y_k) \geq 0$ = Constraint for planned iteration between product design *i* and product portfolio elements *j* for project k

$\gamma_k$ = Mean resource cost rate for product k

$G(z_k, z'_k)$ = Budget cost function for project k

I = Set of product design decision elements

J = Set of product portfolio decision elements

K = Set of product design projects in the product design portfolio

$\lambda_k$ = Function for the number of iterations between the product design portfolio domains for project k

$n_{ij}$ = Binary value indicating dependence between DMM element i and j

$n_{ijk}$ = Binary value indicating dependence between DMM element i and j for project k

$N$ = Total count indicating dependence for all projects within the portfolio

$M$ = Total number of design equality constraints

$p$ = product design material component

$R$ = Total number of product design inequality constraints

$S$ = Vector of portfolio scenario

$t_k$ = design time decision variable for project $k$

$T_k$ = Time horizon for project $k$

$x$ = design material decision variable

$\omega$ = random variable vector that represents the number of iterations

$y$ = binary decision vector

$y_{ijk}$ = binary variable indicating the existence of dependence and iteration between decision elements $i$ and $j$ of project $k$

$y_k$ = binary decision variable indicating the existence of dependence and iteration

$z_k$ = Iterative product design cost function for product $k$

$z'_k$ = Basic design cost function for product $k$

$Z(y,\omega)$ = random vector that represents the simulation outcome

# Chapter 5

# SENSITIVITY-BASED PRODUCT PORTFOLIO AND DESIGN INTEGRATION

In this study we present a novel integration between product portfolio management evaluation criteria and product design decisions involving the design of chemical-based configured consumer products. We consider the variance contribution made by the product's quality characteristics to the product's economic performance that is measured via its net present value (NPV). The sensitivity-based time constrained selection problem (STCSP) is modeled as a static deterministic problem, solved with the objective of mean cost minimization. The STCSP model utilizes a hybrid approach involving the application of Monte Carlo simulation, heuristics and algorithmic processing to optimize the product design planning process. In this approach, product design activities dependencies are modeled as linear inequalities constraints. An industry based case study is used to evaluate the proposed approach.

## 5.1 Introduction

Increasingly, the survival of most firms depends on their ability to innovate, design and develop discrete products at a rate faster than their competitors (Rungtusanatham and Forza 2005). Needless to say, this reality places tremendous pressure on the product design community in particular; requiring them to better plan and manage design activities in order to ensure rapid and cost-effective product introduction. New product introductions are critical to the firm's health and sustained profitability(Clark and Fujimoto 1991). According to (Hoyle and Chen 2007), as much as 75% of committed manufacturing cost can be attributed to decisions made during the product design phase.

However, it is also well recognized that product design is a rather complex process involving cross-functional team participation(Westerberg and Subrahmanian 2000), inherent product complexity and managerial challenges(Aoussat and Christofol 2000). Past and current emphasis on cross-functional coordination via approaches such as concurrent engineering (Koufteros, Vonderembse et al. 2001) indicate a wide recognition of these challenges and complexities. Hence, the utilization of such coordinated approach seeks to guarantee commercial and technical feasibility - such as ensuring the designed product is fit for manufacturing(Tanguy and Marchal 1996; Whitfield, Coates et al. 2000).

Nonetheless, in spite of these efforts the challenge for product designers remains daunting in the face of increasing market uncertainties, rising demand for product variety, and the demand for shorter development cycle time. In response to the market pressures, many firms steer their product development efforts towards less risky new product categories such as product line extensions and product modifications. According to Cooper, R. (1996) the two most risky product categories of “new-to-the-world” and “new-to-the-firm” represent only 30% of new product launches. The adoption of this less risky strategy does not eliminate delays and cost overruns that result sometime from poor product design planning. Irrespective of the new product category, design engineers have long recognized that in-process design decisions contribute significantly to the final design success (Lewis, W. et al. 2006). To aid the design planning and decision process, designers have commonly established engineering priorities by ranking the customer requirements solicited early in the product development process. However, customer requirements captured via voice of the customer (VOC) studies are sometimes misleading, as they do not always reflect the true valuation of product attributes as would be indicated by the customers’ purchasing intent. Furthermore, such approach fails to address the dynamic nature of customer requirements resulting from technological advances and other dynamic market forces. Hence, despite early efforts to incorporate customer requirements, there exists a need for greater focus on the product design planning process as evidenced by the occurrence of costly design iterations, time consuming and costly non-value add design efforts, as well as costly product failure due to improper tradeoff between speed and product quality.

According to (Hoyle and Chen 2007) it is very important that product design decisions are consistent with the firm’s objectives. In general, active product design decisions may include: 1) the selection of a preferred design alternative; 2) the determination of an appropriate design experimentation strategy; 3) identification and selection of product quality characteristics for robust enhancement; 4) specifying robust enhancement strategies; and 5) the selection of product quality characteristics for performance enhancement and validation. Numerous studies have examined the linkage between product design and business decision-making (Georgiopoulos, Jonson et al. 2005; Kumar, Chen et al. 2009) with a bias towards enabling business decision making.

The overall objective of this study is to develop novel decision support systems that provide valuable insight to product designers, therefore enabling optimal product design decision making that leads to efficient product design undertaking. New product portfolio management is a critical business decision making process that determines research and development (R&D) investments, and ultimately decides the firm's performance. The approach also relies on the design independence of unique product attributes. Hence, we apply this approach to the design of specific chemical-based configured consumer products because aspects of their product requirements can be achieved and measured independently. Such products may combine several technology platforms into a single product for specific market application. Furthermore, the proposed approach exploits the interdependence between product design decisions and product portfolio management decisions making in an effort to streamline product design activities. In so doing we examine the sensitivity of a critical portfolio management decision factor in order to specify the initial feasible state of the product design planning problem. A two stage processing-optimization model is employed to: 1) select a feasible set of design operations and 2) to specify an optimal performance-based product design plan.

## 5.2 Background

In this section the relevant literature is reviewed focusing on the integration of decision support tools. In recent decades business process reengineering has been the subject of numerous research studies aimed at achieving optimal cross-functional performance(Tanguy and Marchal 1996). The increasing development and application of integrated decision support models in areas such as supply chain (Rimal, Moon et al. 2008) and research and development (R&D) (Nihtila 1999) are examples of such studies. Moreover, integrated concepts such as concurrent engineering and integrated product development (IPD) have found wide application in new product development efforts across multiple industry sectors (Nahm and Ishikawa 2004). The concurrent product development framework facilitates early interdisciplinary collaboration that ultimately leads to an overall reduction in the development cycle time. Hence, research in concurrent engineering seeks to challenge the sequential linking of functional disciplines, such as R&D, marketing, and manufacturing, while highlighting the productivity benefits realized from a collaborative approach (Tanguy and Marchal 1996; Koufteros, Vonderembse et al. 2001; Yan and Xu 2007). Most of the studies have limited the integration to two disciplines, such as marketing and manufacturing (Sherman, Berkowitz et al. 2005; Michalek, Ceryan et al. 2006; Kumar, Chen et al. 2009) or product design and manufacturing (Nihtila 1999), commonly referred to as the design for manufacturing

(DFM) approach. (Rungtusanatham and Forza 2005) proposed a three dimensional concurrent engineering approach that simultaneously coordinates the product design, manufacturing and supply chain decision. However, the prevailing realities of intense consumer demand for product variety, coupled with the market demand for speed, have rendered these integrated strategies inadequate. While the benefits of concurrent engineering have long been documented in the literature, more recent research studies have considered the effects of integrating aspects of product development with the business decisions making process (Ng 2004; Georgiopoulos, Jonson et al. 2005). The real driver of a firm's competitive advantage, and therefore its survival, is derived from its ability to satisfy its customer and its shareholders. Hence, a technique such as quality function deployment (QFD) that is used to link customer requirements to product design decision has proven to be very valuable to the firm's success. Likewise, it is critically important to ensure that R&D efforts are directly linked to business strategies and reflect existing business priorities. (Ng 2004) noted that the technical objectives of product and process design should be set with the business performance measures in mind. He further went on to propose a hierarchical decision framework that relates business decision-making to the design and development of product and processes. Such framework exploits the difference in scale and length of R&D decisions to yield a hierarchical decision-making structure, wherein regions of scale overlap indicate interaction between the levels.

Other studies have used the overlapping of different functional activities as a time saving mechanism (Krishman, Eppinger et al. 1997; Blacud, Bogus et al. 2009). The forging of inter-functional coordination is only one of the many approaches adopted in new product development industries for speeding up the development efforts. In a recent study, (Langerak and Hultink 2008), investigated nine accelerated approaches applied for reducing development cycle time in 233 manufacturing industries. Among the approaches studied, they have found that improving the speed of tasks or activities was one of the more effective strategies for reducing the development cycle time. (Millson, Raj et al. 1992) in an earlier study also identified the elimination and alignment of new product development activities as important contributing factors to reducing the development cycle time. (Gonzales and Palacios 2002) noted that acceleration of development continues to carry significant strategic importance for the firm. (Poolton and Barclay 1998) further expanded that improved efficiencies in the launching of new products hold the greatest potential for overall improvement. In a recent study, (Meier, Yassine et al. 2007) stressed the importance of appropriate design activities sequencing and utilizes a design structure matrix (DSM) to streamline information between product design activities.

In other studies, (Ni, Luh et al. 2008) addressed the design scheduling problem by explicitly modeling tasks dependencies along with analysis of related communication activities. The unique project scheduling problem was formulated as a deterministic model that utilizes Lagrangian relaxation and applied heuristics. Other application of Lagrangian relaxation in project scheduling has been shown to combine stochastic dynamic programming in order to handle uncertainties in task duration (Luh, Chen et al. 1999) . Although limited in its application, deterministic approaches such as branch-and-bound (Nazareth, Verma et al. 1999; Heilmann 2003) and genetic algorithms (Hartman 1998; Meier, Yassine et al. 2007) have found wide application in project scheduling problems. Furthermore, although computationally efficient, the application of heuristic procedure by itself jeopardizes the quality of the results (Ni, Luh et al. 2008). However, a combined heuristic-optimization procedure offers a more realistic tradeoff between the practicality and the accuracy of the method. In other studies the combination of simulation and mathematical programming techniques have been used to assess uncertainty encountered in R&D pipeline and further led to control of the corresponding risks (Subramanian, Pekny et al. 2000).

In this study we have expanded the concept of sensitivity in design to investigate the product design–portfolio management interface. In so doing we apply a hybrid computational architecture that utilizes priority rule-based procedure in an effort to streamline product design operations. The procedure may employ a serial or parallel scheme to schedule the product design activities.

This chapter is structured as follows. A general overview of the product design planning problem is first outlined. This is followed by a system description and a description of the solution's approach used to solve the integrated problem in sections 5.4 and 5.5, respectively. The problem formulation is presented in section 5.6. An industrial case study is considered in section 5.7 to illustrate the application of the proposed approach.

## 5.3 The Product Design Planning Problem Description

The deterministic product design planning problem involves the prioritization of product design objectives and the assignment of product design activities. Such assignment is governed by appropriate precedence and resource constraints. In this study, the application of product design activities towards a performance-based design objective is defined as a design operation. For a given product design problem, all such design operations must be undertaken within a pre-determined time span. The optimization problem is therefore a time constrained selection problem (TCSP). The proposed study utilizes the simulated product performance to obtain the sensitivity relationship between the product performance attributes (product design domain) and the product economic value (portfolio management domain) to determine the feasible set of product design operations. Hence, the impact of product's quality performance variability on changes in product valuation is obtained as a sensitivity measure.

A schematic diagram representing the flow of information between the product design and product portfolio management domains is presented in Figure 5. 1.

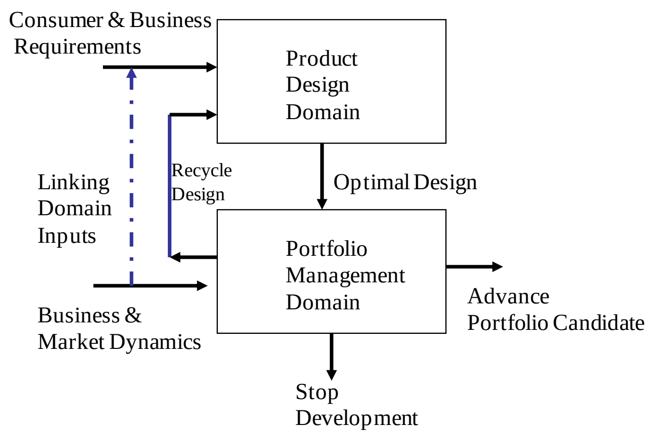



Figure 5.1: Schematic of Product Design- Portfolio Integration

In practice, the product design problem involves the translation of consumer and business requirements into optimal product design specifications. However, the design planning aspect ensures adequate resource assignments to the various product design operations necessary to obtain the optimal design specifications. Ultimately, the optimal design specification, along with its accompanying business case, advances for review and selection consideration within a new product portfolio context. Given a set of product design projects and limited resources, decisions are made concerning individual projects whether to advance, recycle (re-worked) or stop all product development efforts. Hence, advanced and recycled projects are assigned resources in order to pursue further development or repeat prior design efforts respectively. Such design iterations represent an inefficient use of the firm’s resources and can lead to cost and schedule overruns for the specific project as well as other projects within the design phase. Among the critical portfolio management decision considerations is the potential economic value (net present value) of individual product design projects. Appropriate alignment of the two domains, based on this portfolio metric, provides insights that influence product design decision considerations and ultimately leads to identifying the optimal set of product design operations.

Product design operations feasibility and rearrangement policy are based on the sensitivity analysis result obtained from modeling the economic value as a function of the product quality characteristics. The rearrangement objective is to reduce product design cost and lead time by focusing first on the most critical product quality performance characteristics. In this study, combined measures of the product quality characteristics are used to assess the overall product's performance. Monte Carlo simulation of the product's economic performance generates product performance scenarios for which economic values are obtained. Uncertainties in the product's economic performance due to market variability are assumed to be directly linked to variability in product's performance. The integrated product design planning problem is modeled as a discrete event that interfaces with the product portfolio management process. In this instance, a single cycle (static) system illustrates the interaction of the two domains at their interface. The underlying assumption in this study is that better understanding of the relative importance of quality characteristics enables appropriate prioritization that leads to the devising of appropriate experimentation, testing evaluation and robust design strategies to enhance design performance. A standard sensitivity analysis study to indicate the variance contribution of the product quality characteristics to the product's economic value (NPV) forms the criterion for defining and prioritizing the product design decisions.

## 5.4 Model Description

In this chapter we consider the design of a single product that takes place within a finite time period *T*. The state of the design is characterized by a set of discrete design activities, $A \equiv \{a_i \mid i = 1, \cdots\cdots n\}$, and product design performance objectives evaluated via a set of product quality characteristics, $Q \equiv \{q_j \mid j = 1, \ldots\ldots m\}$. These product design performance objectives are subsequently prioritized and may undergo preliminary screening to yield an indexed set N such that $N \subseteq Q$. The application of a set of design activities to a set of product quality characteristics defines the set of design operations, U. The initial state of the product design planning problem, as specified by the new product category, comprise the full set of all potential product design performance objectives. We assign a {0,1} value to indicate the existence of a design operation. Hence, each ordered pair $\{i\ ,j\}$ for the initial design planning problem assumes the value 1 in this instance. The set F is the processed set of product quality characteristics such that $F \subseteq U$. Furthermore, sensitivity-based priority rule govern the sequence of these design operations. The product design problem is decomposed into design sub-problems that can be solved independently to obtain specific product performance objectives (product quality characteristics measures), subject to a deterministic time constraint.

The overall objective of the product design planning process is to streamline product design operations in such a way that minimizes the total design costs while satisfying potential market preference. The streamlining of design operations also implies reduction in possible sunk cost in the event that the project is later canceled. Conversely, reduction in cycle time, resulting from the elimination of non-value add design operations, leads to greater revenue generation over the life cycle of the product in the event the product survives to market launch. The proposed approach assumes there exists no limitation on the availability of skilled resource necessary for carrying out the design operations within the specified time span. The time span $T$ assigned for the design of the single product is estimated based on the initial feasible state matrix of the product design operation coupled with product designer's knowledge of the development of similar product within the product line or within the market. An illustration of the system's execution structure is presented in Figure 5.2.

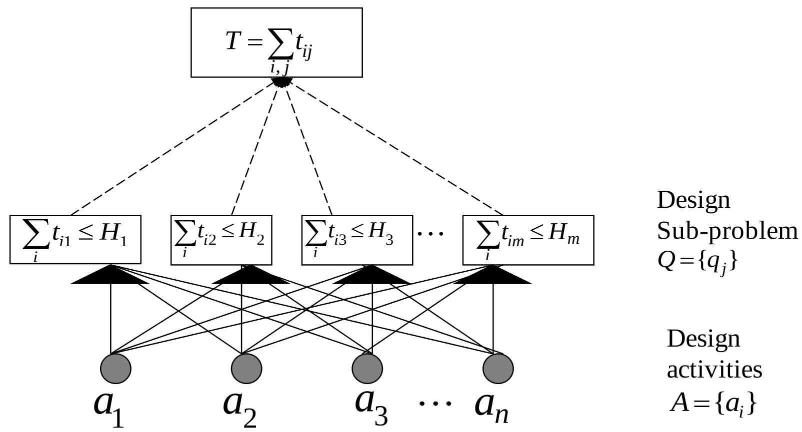



Figure 5.2: Design Operation Architecture

The approach assumes linearly independent, sequentially ordered design operation that targets specific design objective. However, such approach is further constrained by inherent design activity dependence or mandatory requirements. The magnitude of the connection is characterized by the expected time duration, $t_{ij,}$ in which a given activity $i$ is applied to quality performance characteristic $j$. $H_j$ denotes an upper bound on the design time necessary to yield the specifications for product quality characteristic $j$.

## 5. 5 The Solution Approach

The proposed two-stage processing-optimization model prioritizes and streamlines product design operations in an effort to reduce overall design cost and cycle time. Vector set **S** represents the set of product performance scenarios (measured via quality characteristics values) generated randomly using Monte Carlo simulation technique.

Sensitivity analysis yielded the relative variance contribution of each quality characteristics to the net present value (NPV), thus providing the basis for prioritization. We utilize a mapping scheme wherein each quality characteristic $j$ is assigned a unique dummy value $r_j$ to denote its priority position deduced from its relative variance contribution. The remaining processing actions in stage 1 involve establishing an initial feasible set of design operations for the second stage optimization problem. The computing architecture for the sensitivity-based time constrained selection problem (STCSP) is given in Figure 5.3.

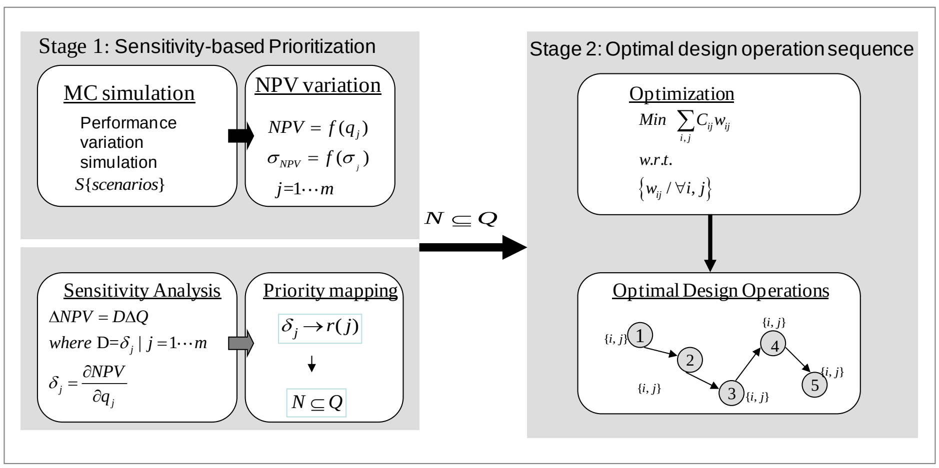



Figure 5.3: Schema of the Solutions Approach

According to (Kolisch 1996) there are two components of the priority based scheduling scheme approach: 1) the schedule generation scheme and 2) a priority rule. Such schedule generation scheme may follow a serial path or a parallel path. We begin the product design problem planning problem with a pre-determined set of product quality characteristic. The set of first stage operations in the solution approach (Figure 5.3) yield a priority indexed set of product quality characteristics obtained by applying a priority rule that assigns higher priority to quality characteristics associated with greater variance contribution. The model allows for product design planning flexibility in that it allows designers to reduce the "initial state space" by applying a variance contribution threshold value B. The variance threshold value B specifies the lower bound of the quality characteristics variance contribution such $\delta_j \geq B$ for all *j*. However, such screening of quality characteristics would be subjected to technical product performance requirements. In this study we adopted and modified the serial approach first proposed by (Kelley 1963). We proposed a nested selection procedure with an objective to select a set of product design operation that satisfies the priority rule and the set of design activities constraints. We specify the selection problem by denoting a maximum number of *m* stages, such that $k=1.....m$, and each stage *k* accompanies the selection of a product quality characteristic *j* from the indexed set N. The selection of the product quality characteristic is done based on assigned priority value ( $r_j$ ) and is followed by assignment of product design activities according to the activity relationship and resource constraints. Associated with each stage is a processed set of product design objectives $F_k$ and an unprocessed set $Y_k$ of relatively lower prioritized design objectives member. The algorithm selects the product quality characteristic from the set $Y_k$ and assigns design activities until all members are assigned or until resources are depleted. Figure 5.4 summarizes the algorithm used for stage 2 in the proposed framework.

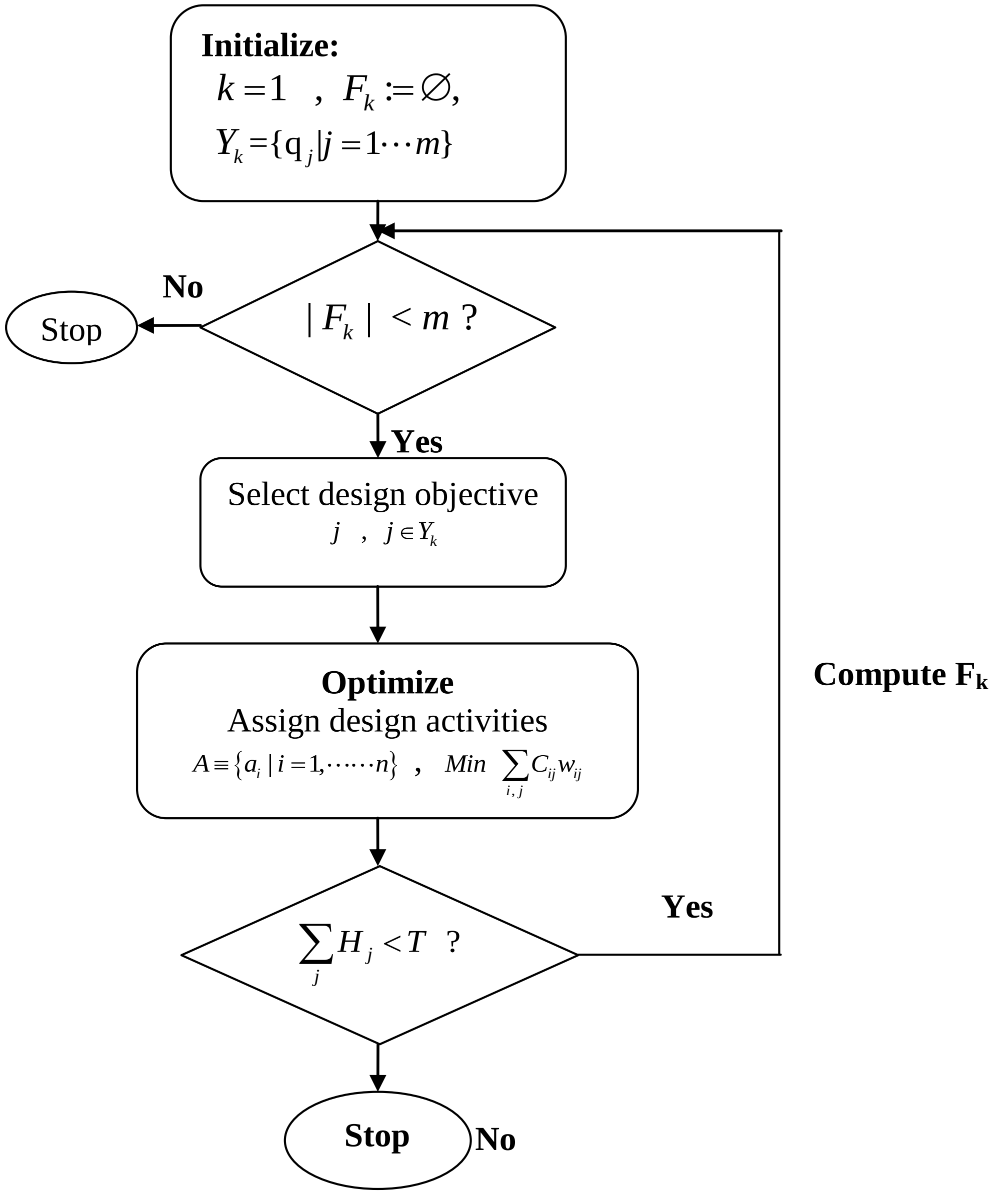



Figure 5.4: Algorithm for Stage 2 of STCSP

5. 5. 1 Product Economic Performance Sensitivity

In this study we relate the product performance attributes (product quality characteristics) to the product economic value in order to assess variance contribution and subsequently assign priority to individual product performance objective. This approach exploits the underlying link between customer preference and the product's attributes that are specified during product design. Theoretical basis for this relationship can be found in an earlier work (Oliva, Oliver et al. 1992) in which it was demonstrated that consumer demands depend on the level of product performance. Consequently, we express the estimated product's profit, P as a function of the market demand, which in turn is given as a function of the product performance product quality characteristics such that

$$P = P(D') \tag{5.1}$$

where $D'$ is the product demand

We apply a simple linear demand model developed by (Cook and Wissmann 2007) for the single product:

$$D' = K(V(q) - p) \tag{5.2}$$

where, K is the absolute elasticity of demand and *V(q)* is the product value; *q* is the product quality characteristic. A slightly modified expression for product value (de Weck 2006) is made to omit product option :

$$\mathrm{V}(q_1, q_2 \cdots q_m) = \mathrm{V}_o v(q_1) v(q_2) \cdots v(q_m) \tag{5.3}$$

where $V_o$ represents the value of the baseline or average product in a given market segment; $v(q_j)$ is given as the value curve for the *j* quality characteristic which is defined as follows:

$$v(q_j) = \left[ \frac{(q_c - q_{ideal})^2 - (q_j - q_{ideal})^2}{(q_c - q_{ideal})^2 - (q_o - q_{ideal})^2} \right]^{0.5} \tag{5.4}$$

where $q_c$ is assigned the critical threshold value. Hence the market demand depends on the product value which effectively indicates the distance between the firm's product quality characteristic and the ideal level in terms of customer preference.

The variation in the product quality characteristics is modeled by mapping the product attribute space to the product economic value space by employing the Monte Carlo simulation method. An appropriate probability distribution, based on historical data or expert knowledge was assigned to each input quality characteristic variable. Such mapping utilizes the functional form of the product performance economic value given as:

$$NPV = \frac{P_t(p, D')}{(1+r)^t} \tag{5.5}$$

where NPV is the net present value, $P_t$ is the net cash flow (profit) at time *t*, *t* is the time of the cash flow and $r$ is the discount rate. Sensitivity analysis was performed to assess the impact of the variation of the product quality characteristic on the product economic performance by calculating a multi-year NPV.

## 5.6 Optimization Problem Formulation

In this section we introduce the notations and the deterministic optimization model for the cost minimization problem. In this formulation it is assumed that time resource associated cost is the major cost contribution during this development phase. With the product requirements defined, the product design activities $\forall a_i \in A$ can be grouped into the following categories:

1. Modeling of product performance
2. Design optimization
3. Testing or validation of product's performance
4. Control of product performance

In this study the actual product performance is obtained by evaluating the set of product quality characteristics, $Q \equiv \{q_j \mid j = 1, \ldots\ldots m\}$ that provides a quantitative measure. The product design planning process involves assigning design activities aimed at specific product performance objective and ensure that such activities are undertaken and completed within a given time allocation. The time allocation is determined based on historical knowledge or product designer's estimation. In this study such activity assignment is influenced by the sensitivity-based priority associated with the product performance objective. A general form of the optimization problem is given as follows:

$$
\begin{aligned}
&Min\ z=\sum_{i=1}^{n}\sum_{j=1}^{m}c_{ij}w_{ij}\\
&Subject\ To:\\
&\sum_{i=1}^{n}t_{ij}w_{ij}\leq H_j \qquad \forall j\\
&\sum_{j}H_j\leq T\\
&w_{ij}\in\{0,1\} \qquad \forall i,j
\end{aligned}
\tag{5.6}
$$

where: $c_{ij}$ is the cost incurred when activity *i* is applied to quality characteristic *j;* $w_{ij}$ corresponds to the binary decision variable which is 1 if activity *i* is applied to quality characteristic *j*, 0 otherwise, $t_{ij}$ = is the time duration of activity *i* when applied to quality characteristics *j;* $H_j$ is the time resource allocated for quality characteristic *j* with $H_j > 0$, and $T$ is the total time horizon for the overall design problem.

The design planning problem is further constrained by design activity relationship requirements along with quality characteristics priority index.

There are product design activities whose execution is dependent on the existence of another. This requirement is accounted for in the formulation problem by specifying the following:

$$\alpha_{id} = \begin{cases} 1 \ if \ \ activity \ i \ is \ required \ for \ executing \ activity \ d \\ 0 \ otherwise \end{cases}$$

$$\begin{aligned} & w_{ij} - w_{dj} \geq 0 \qquad \forall_{i} \ , \alpha_{id} = 1 \\ & w_{ij} \in (0,1) \qquad \forall_{i,j} \end{aligned} \tag{5.7}$$

The mandatory design activity is specified in the problem formulation as follows :

$$M_{ij} = \begin{cases} 1 \ if \ \ activity \ i \ for \ the \ j \ quality \ characterisic \ is \ mandatory \\ 0 \ otherwise \end{cases}$$

$$w_{ij} > 0 \ where \ M_{ij} > 0 \tag{5.8}$$

The sensitivity analysis provides the basis for the priority policy governing quality characteristic precedence.

If there are design operations that occur and are mutually exclusive, the following constraint is enforced;

$$\sum_{i,j \in \Omega} w_{ij} \leq 1 \tag{5.9}$$

where $\Omega$ is a set of mutually exclusive design operations.

## 5.7 Industrial Case Illustration

Unique performance requirements for the pressure sensitive adhesive (PSA) label product can be determined via discrete and independent development that may require specialized resource allocation. The multi-lamination PSA product consists of an adhesive layer applied to a polymeric film backing and a release liner coated with silicone release agents. The PSA label product is designed for personal care consumer products labeling application, with discrete performance requirements, and is therefore classified as a chemical-based configured consumer product. The product design problem involves the evaluation and specification of individual layer or composition properties such as mechanical strength property, ink adhesion property, adhesive bond strength and label aesthetic properties. We provide an example illustration of the sensitivity-based time constraint selection approach (STCSP) by exploiting the decomposable performance-based construction of the PSA label product.

The quality of the product is defined by a set of discrete measurable characteristics of quality, $Q \equiv \{q_j \mid j = 1, \ldots\ldots 7\}$. The ultimate objective of this design effort therefore is to independently optimize the quality characteristics by performing a set of design activities $A \equiv \{a_i \mid i = 1, \cdots\cdots 4\}$. The design activities may involve robust enhancement, pilot scale and manufacturing scale evaluation as well as unique or extended field trial evaluation. Such targeted design efforts consumes resources in the form of additional materials and people resources. Hence, the design planning problem yields the optimal set of design operations with their corresponding expected costs and time duration.

5.7.1 Monte Carlo Simulation and Sensitivity Analysis

Each product quality characteristic has estimates of statistical parameters and assumed normal probability function. The product quality characteristics are unique measures of independent layer sub-system that delivers unique functional and aesthetic performance. Table 5.1 summarizes the base values and statistic used in the Monte Carlo simulation

**Table 5.1: Basic Performance Values**

| *Product Quality Characteristics* | *Mean Values* $\mu$ | *Standard Deviation* $\sigma$ |
|---|---|---|
| $q_1$ | 3.2 | 0.3 |
| $q_2$ | 16500 | 1650 |
| $q_3$ | 0.03 | 0.003 |
| $q_4$ | 35 | 3.5 |
| $q_5$ | 50 | 5 |
| $q_6$ | 0.83 | 0.08 |
| $q_7$ | 3000 | 300 |

Monte Carlo simulation process occurs by random sampling probability distribution functions (pdfs) using random number generation to create artificial history of product performance data. Commercially available simulation module (Crystal Ball) performed a fixed simulation of a length of 1000 trials. The random numbers generated were used to calculate the NPV output values.

Sensitivity analysis is performed to evaluate the relative variance contribution of each product quality characteristic as shown in Figure 5.5, with the range of uncertainty associated with each quality measure.

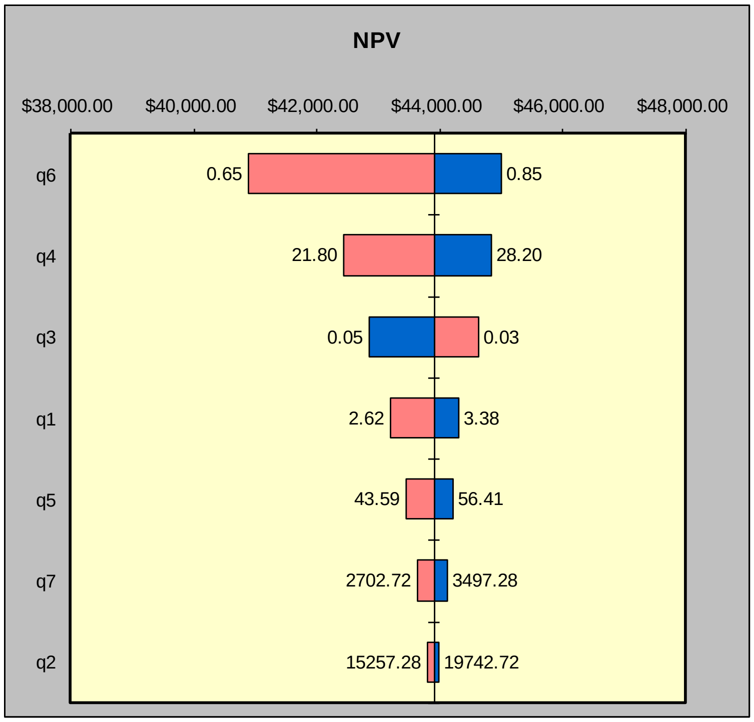



Figure 5.5: Product Quality Characteristic Variance Contribution

The product quality characteristics are prioritized to differentiate their impact on the product economic value (NPV). Hence, the heuristics derived from this analysis specify that product quality characteristics should be prioritized based on the corresponding NPV sensitivity value. The model uses a normalized function for which linear weights are assigned to each quality characteristics such that $q_j$ is associated with a value $r_j$, where $\sum_{j=1}^{m} r_j = 1$ as given in Table 5.2.

**Table 5.2: Sensitivity Based Assigned Priority of Quality Characteristics**

| $q_j$ | $q_1$ | $q_2$ | $q_3$ | $q_4$ | $q_5$ | $q_6$ | $q_7$ |
|---|---|---|---|---|---|---|---|
| $r_j$ | 0.1 | 0.002 | 0.2 | 0.26 | 0.068 | 0.36 | 0.03 |
| **Priority Assignment** | 4 | 7 | 3 | 2 | 5 | 1 | 6 |

Figure 5.5 illustrates the relative impact of the quality characteristics on the portfolio decision criteria measure (NPV) for the given probabilistic assumptions with a base case of $44,000.00. The relative sensitivity values are used to assign a priority index to the quality characteristics in an effort to streamline design operations. Although widely used, economic models such as NPV have limited utility in assessing the value of products of all new product categories. Consequently, such models are considered to be most relevant for line extension and product modification projects for which some familiarity exist (Cooper, Egdett et al. 2001). Therefore, since the sensitivity-based optimization framework utilizes such economic model, similar limitations apply. Nonetheless, this approach provides valuable insight into the relative importance of design actions and therefore enable better planning within the given time horizon.

5.7.2 Optimization Problem

For a given un-ordered set of design activities, priority indexed product quality characteristics and corresponding expected design operations time duration and cost, we solve a linear programming (LP) optimization problem for the incremental product design determine as given in problem 5.10.

$$
\begin{aligned}
&Min\ z = \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij} w_{ij} \\
&Subject\ To: \\
&\sum_{i=1}^{n} t_{i1} w_{i1} \le 1.4 \qquad \forall j \\
&\sum_{i=1}^{n} t_{i2} w_{i2} \le 0.6 \\
&\sum_{i=1}^{n} t_{i3} w_{i3} \le 0.3 \\
&\sum_{i=1}^{n} t_{i4} w_{i4} \le 0.4 \\
&\sum_{i=1}^{n} t_{i5} w_{i5} \le 0.5 \\
&\sum_{i=1}^{n} t_{i6} w_{i6} \le 0.5 \\
&\sum_{i=1}^{n} t_{i7} w_{i7} \le 0.3 \\
&w_{ij} \in \{0,1\} \qquad \forall i, j
\end{aligned}
\tag{5.10}
$$

The optimization problem was constrained by a set of linear inequality constraints that 1) established activity precedence for the set of design activities (2 accounted for mandatory requirements and 3) accounted for activity precedence requirements. To highlight the effect of the proposed approach we compare a worse case product design effort, wherein all product design operations were executed such that, $w_{ij} = 1, \quad \forall i, j$ .

It is the authors' viewpoint that the worse case approach is likely the most commonly practiced in industry due to the inability to make intelligent prioritization of design criteria.

The optimal set of product design operation given in Table 5.3 yield a total expected cost of $29,540.00 and time duration of 2 months.  This compares with the worse case of 3.2 months duration and a corresponding cost of $42,460.00.  This value of 3.2 months is a conservative estimate as it does not account for time taken for iterations between design tasks. The ability to determine critical quality characteristics based on their value contribution, enables efficient resource allocation that results in important cost savings. Conversely, there is a high probability to "over-design" a product offering in absence of clear alignment of design attributes to purchasing intent. Hence, R& D organizations expend significant resources in pursuing non value-add or limited value-add activities that yield little or no return on investment (ROI).

**Table 5.3: Optimal set of Design Operations**

| | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
|---|---|---|---|---|
| $q_1$ | 1 | 1 | 1 | 0 |
| $q_2$ | 1 | 0 | 0 | 0 |
| $q_3$ | 1 | 1 | 1 | 1 |
| $q_4$ | 1 | 1 | 1 | 1 |
| $q_5$ | 1 | 0 | 1 | 0 |
| $q_6$ | 1 | 1 | 1 | 1 |
| $q_7$ | 1 | 0 | 0 | 0 |

## 5. 8 Conclusions

The sensitivity-based design operation selection framework presented in this chapter provides an efficient platform for design planning. By utilizing the sensitivity relation between the product design domain and the portfolio management domain, appropriate focus was directed towards optimizing the more critical product performance objectives. Hence, minimizing the cost and time allocated to non-value add product design operations.

Furthermore, this approach enables product designers to integrate the voice of the market directly into the product design process based on the more reliable indicator of purchasing intent. Also, early and deliberate collaboration between the technical community and marketing facilitate greater market acceptance at the point of product launch and therefore increases the probability of product success. Altogether, the presented results underline the potential of the STCSP approach to aid product design planning problem for real world application.

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## **5. 9 List of Notations**

A = Set of product design activities

$a_i$ = Product design activity *i*

$\alpha_{id}$ = Indicate dependence of activity *i* on activity *d*

B = Assigned lower bound variance contribution index ( product design objectives with variance contribution below this value may not be assigned design activity resources)

C = Product variable cost

$c_{ij}$ = Cost incurred when activity i is applied to quality characteristic *j*

D =Set of NPV sensitivity coefficients

$D'$ = Product demand

$\delta_j$ = NPV sensitivity coefficient for quality characteristic *j*

F = Set of processed product design objectives

$F_k$ = Set of process product design objective associated with stage k

$H_j$ = Upper bound on design time assigned to quality characteristic *j*

*i* = Index for product design activity

j = Index for product quality characteristic

| | |
|---|---|
| k | = Quality characteristic selection stage in the recursive solution approach of the STCSP |
| K | = The absolute elasticity of demand |
| m | =Maximum number of product quality characteristic and number of selection stages of quality characteristic |
| $M_{ij}$ | = Indicate whether activity *i* is mandatory for quality characteristic *j* |
| N | = Priority indexed set of product design objectives |
| n | = Number of product design activities |
| P | = Product profit |
| p | = Product price |
| $P_t$ | =The net cash flow at time *t,* |
| Q | =Set of product design objective or quality characteristics |
| $q_j$ | = $j^{th}$ quality characteristic |
| $q_c$ | = Assigned as a critical threshold value |
| *r* | =Discount rate |
| $r_j$ | = Assigned priority value to product quality characteristic *j* |
| S | = Simulated scenario of product performance |

$t$ =The time of the cash

$t_{ij}$ = The time duration of activity *i* when applied to quality characteristics *j*

$T$ =Product design time horizon

U = Set of product design operations

V(q) =The product value

$V_o$ =The value of the average product in a given market segment

$v(q_j)$ =The value curve for the *j* quality characteristi*c*

$w_{ij}$ = Binary decision variable that indicate the application of design activity *i* to product quality characteristic *j*

$Y_k$ =Unprocessed set of product quality characteristics

z = Cost objective function

# Chapter 6

# SUMMARY AND FUTURE WORK

The development and application of novel decision support models to enable efficient product design planning, selection and execution, is the unique contribution of this work.

The uniqueness of the proposed methodologies relates to the application of multidisciplinary integration and the exploitation of the implicit relationship between the product design and product portfolio management domains in particular. Hence, we have expanded product design interaction beyond the interplay of design activities to the integration of functional domains for greater effects.

In this study we use the dependency matrix approach to illustrate domain relation between the product design and product portfolio management domains, and to facilitate their integration. Moreover, the solution approach integrates the stochastic effects by simulating random patterns of integration that characterizes the product design-product portfolio interaction. In other application, we consider the variance contribution made by product quality characteristics to the product's economic performance as the basis for the domains integration. The sensitivity relation enables product designers to prioritize their independent product design objectives resulting in improved resource utilization.

In addition to the primary objective of achieving efficient operation, chemical producers must ensure that the designed product delivers consumer value. We offer a novel consumer integrated product design (CIPD) framework to facilitate the generation of efficient product design solutions via mechanism that explicitly incorporates consumer input and economic criteria. Such explicit incorporation of two competing objectives, in a bi-objective formulation, ensures consumer influence in design tradeoff considerations.

The application of such integrative product design solution approaches offers an innovative response to the increasing market demands for speed and value, while satisfying business need for efficient resource allocation. Included in the features of these novel support systems are inherent designer flexibility to allow for discretionary selection of product design activity along with limited scalability of the proposed approaches.

In this work, we have treated the modeled systems as a static system to focus on the interfacial interactions. For future study we proposed the modeling of a dynamic system representing multiple time periods of the product design process integration. The application of more rigorous stochastic models would necessarily accompany such dynamic process as a critical component of future work. Future work will include the models to include parallel scheduling scheme for enhanced process efficiency.

# Chapter 7

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# Chapter 8

# APPENDICES

## 8.1 Performance Validation of Optimal Product

Figure 8.1 compares the flow curves of the commercially available formulation with that of the optimally designed product. In Figure 8.1 it is shown that both samples exhibited shear thinning behavior, with the optimally designed product yielding a slightly higher viscosity over the shear rate range. The commercially available product and the optimally designed product exhibited similar response in flow properties over the specified range of shear rate. At an application shear rate of $1027 s^{-1}$ viscosity values of 0.44 Pa.s and 0.35 Pa.s were obtained for the optimally designed product and the commercial product respectively. Viscosity value of 0.025 Pa.s has been reported for cream cosmetic product at the much higher shear rates of $5000\ s^{-1}$ and at shear rate of $1000\ s^{-1}$ for less viscous lotion products (Wibowo and Ng 2001). According to (Herh, Tkachuk et al. 1998), the flow properties of cosmetic product strongly influences its acceptance. Furthermore, a product's flow curve provides important information about its storage stability, processing conditions as well as its end-use application (Herh, Tkachuk et al. 1998).

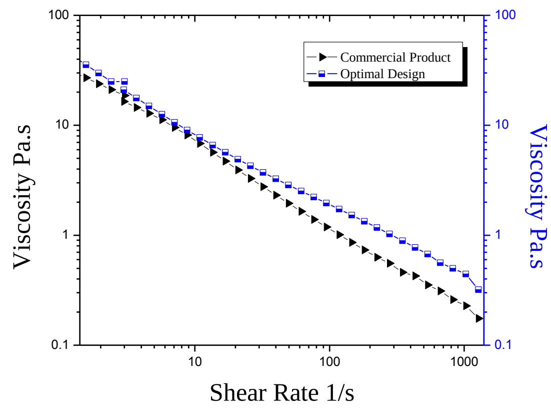


Figure 8.1: Comparison of Flow Curves

In addition to studying the products flow properties, dynamic oscillation testing was also undertaken to compare the underlying microstructure of the under eye cream products. Initial strain sweep was used to determine the viscoelastic region for the under eye cream products. Figures 8.2 and 8.3 compared frequency sweep performed in the linear viscoelastic region for the optimally designed product and the commercial product respectively.

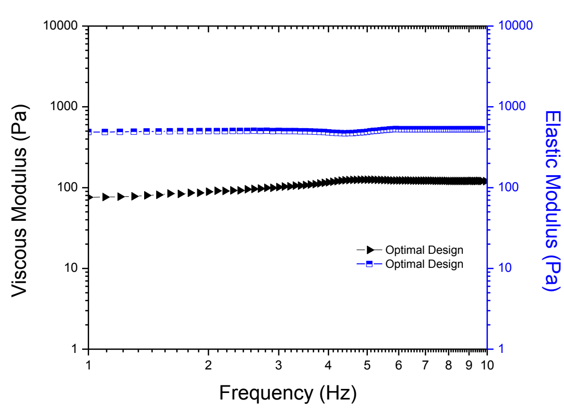


Figure 8.2: Frequency Sweep of the Optimally Designed Product

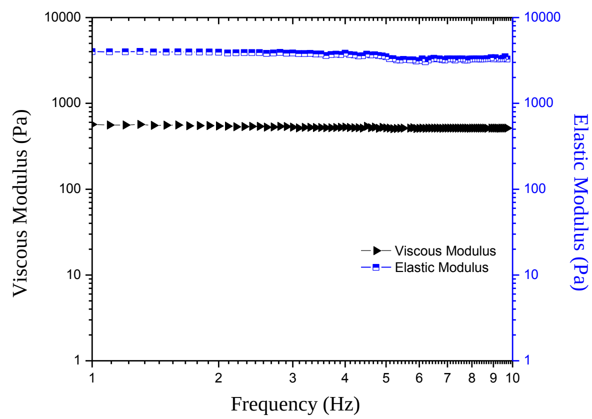


Figure 8.3: Frequency Sweep of Commercially Available Product

A comparison of the two cream products revealed a difference in their underlying microstructure. The commercially available cream has higher storage and loss modulus when compared to the optimally designed product. The difference in internal network structure can be due to difference in compositional variables. The Deborah number ($N_{De}$), which provides an indication of the material's viscoelastic property (Wibowo and Ng 2001) is determined as the ratio of the two moduli (Reiner 1964). The viscoelasticity measured as the ratio of $G'$ (the storage modulus) to $G''$ (the loss modulus) were found to be 4.9 and 6.8 for the optimally design product and commercial product respectively. Hence, both products exhibited greater elastic like behavior over the frequency sweep range with values similar to those reported in the literature (Wibowo and Ng 2001).

## 8.2 Intraclass Correlation (ICC) Reliability for Subjective Measurement

The follow statistical analysis was performed for the subjective consumer rating of the under eye cream product.

**Table 8.1: Subjective Measure Reliability Statistics**

| No. of judges (k)=5<br>No. of samples (n)=8 | SS | DF | Mean Square | Components |
|---|---|---|---|---|
| Judges | 38.35 | 4.00 | 9.59 | JMS |
| Between Samples | 259.82 | 7.00 | 37.12 | BMS |
| Total | 358.29 | 39.00 | 9.19 | |
| Within Samples | 98.47 | 32.00 | 3.08 | WMS |
| Error | 60.12 | 28.00 | 2.15 | EMS |

ICC Reliability-Individual

$$\frac{BMS - EMS}{BMS + (k-1)EMS + k(JMS - EMS)/n} = 0.7$$

ICC Reliability -Average

$$\frac{BMS - EMS}{BMS + (JMS - EMS)/n} = 0.92$$

Both ratings meet the reliability index requirement of $\geq 0.7$

## 8.3 Transformation of Non-Normal Data

Transformation of the dependent variables was undertaken prior to model generation to ensure adherence to underlying assumptions (for the regression model) of normally distributed residuals with constant variance.

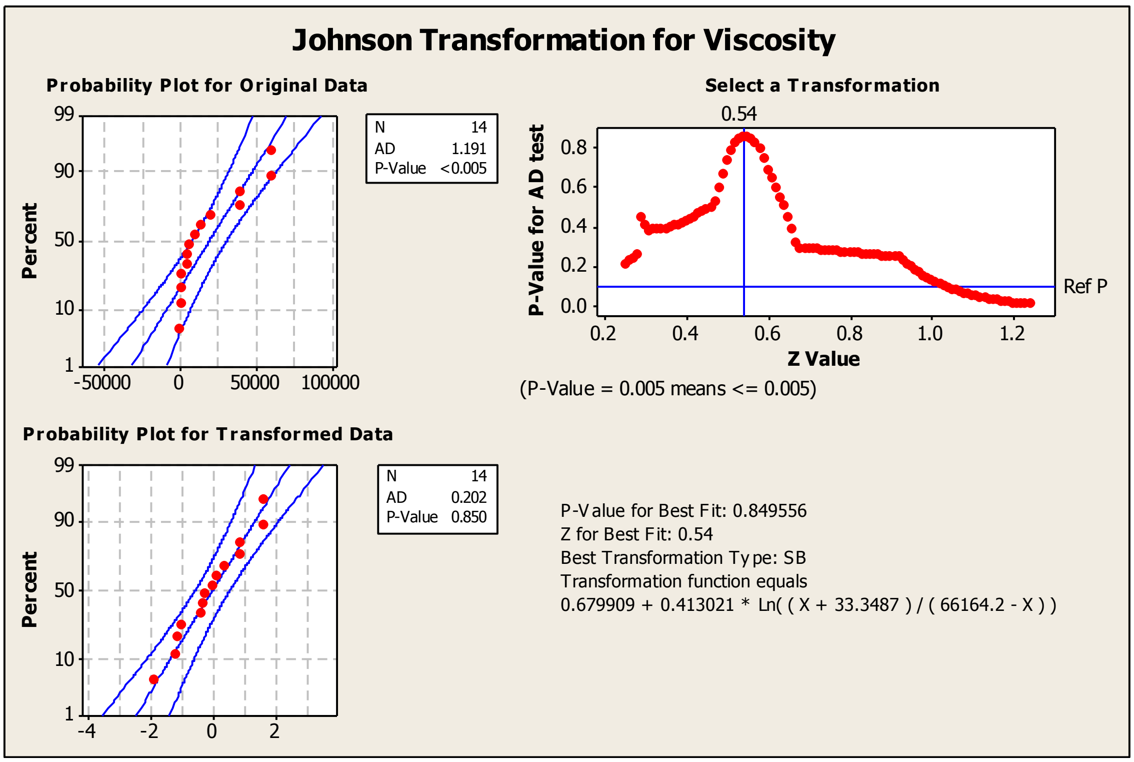


Figure 8.4: Johnson Normality Transformation for Viscosity Data

# CURRICULUM VITAE

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| 01/2007 | 10/2010 | Ph.D. Chemical and Biochemical Engineering<br>Rutgers, The State University of New Jersey |
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## PUBLICATIONS & PRESENTATIONS

Smith, B. and Ierapetritou, M.G. Sensitivity-Based Product Portfolio and Design Integration, Submitted for Publication, *Ind. Eng. Chem. Res.*, June ***2010***

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Smith, B. and Ierapetritou M.G., Framework for Consumer-Integrated Optimal Product Design, *Ind. Eng. Chem. Res****.,*** 2009***, 48*** **(18), pp 8566–8574**

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