A VALUE DRIVEN DECISION SUPPORT FRAMEWORK FOR THE FRONT-END PRODUCT DESIGN AND DEVELOPMENT

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*"Now the general who wins a battle makes many calculations in his temple ere the battle is fought. The general who loses a battle makes but few calculations beforehand. Thus do many calculations lead to victory, and few calculations to defeat: how much more no calculation at all! It is by attention to this point that I can foresee who is likely to win or lose."**

**Sun Tzu in "The Art of War"*
Translated by Lionel Giles

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I count myself in nothing else so happy, as in a soul remembering my good friends.*

**** William Shakespeare in "Richard II"***

ABSTRACT

Value-attribute models are used at the front-end phase of the customer driven product design to support the design decision making by eliciting customer preferences. Currently used models are not capable of handling the high dimensional technological product attribute data, plagued by the multicollinearity, with limited observations. Furthermore, they are not equipped to deal with the heteroscedasticity and the dynamic nature of the technological product market systems. As a result, especially, the technological products with longer design cycle times are heavily affected by model uncertainties coming in various faces.

Robust, dynamic, value-attribute models are needed to accurately replicate the market systems, to overcome the deficiencies of the data, and ultimately, to predict the future product values for the front-end concept screening. Therefore, a strategic decision support framework is proposed in this thesis to integrate the hitherto overlooked time variant properties of preferences, into the front-end design decision making process. In the proposed framework, the Partial Least Squares Regression and Path Modelling techniques, robust soft modeling methods, are used as the main decision support tools. And, Customer Revealed Value, a perceived value estimation obtained from a demand-price analysis, is used as the design objective.

There are four main contributions in this thesis. Firstly, a theoretical basis is provided for the multivariate modeling of the value-attribute relationship. Secondly, a robust Partial Least Squares algorithm is introduced to handle the heteroscedasticity presence in the market systems. Thirdly, a dynamic value-attribute model is formulated by combining Partial Least Squares and Time Series Forecasting techniques. Finally, a dynamic value-characteristic model is formulated by extending the earlier model by including higher or system level product characteristics, using Partial Least Squares Path Modeling. All the contributions are validated using the US automobile market data. And, the results of the case studies depict the potential of the framework as a design decision support method.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

GLOSSARY

CA	Conjoint Analysis
Com	Communality Index
CRV	Customer Revealed Value
DA	Damped Additive
DCA	Discrete Choice Analysis
DES	Double Exponential Smoothing
Gof	Goodness of Fit
LV	Latent Variable
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
MV	Manifest Variable
PCA	Principal Component Analysis
PCR	Principal Component Regression
PDD	Product Design and Development
PLSPM	Partial Least Squares Path Model
PLSR	Partial Least Squares Regression
Q^2	PLSR Goodness of Prediction
R^2	PLSR Goodness of Fit
RUM	Random Utility Modeling
RVM	Revealed Value Modeling
SES	Single Exponential Smoothing
VIP	Variable Importance for Projection

NOMENCLATURE

α, γ	DES Weights
$\boldsymbol{\beta}_{ij}$	Inner path coefficients connecting latent variables *i* and *j*
$\boldsymbol{\theta}$	Variance Parameters Vector
σ	Standard Deviation
a	Index of PLS Components (a=1,2,…..,A)
B	PLS Coefficient Matrix
$\mathbf{c}_i$	**Y** Weights of i^{th} PLS component
D	Demand of a product
E_1	Ratio of price elasticity
E_2	Price elasticity of the market segment
F_t	Forecast for Time t
g	Level of an attribute
g_0	Baseline Level of an attribute
g_C	Critical Level of an attribute
g_I	Ideal Level of an attribute
K	Partial derivative of demand with price
k	Index of **X** Variables (k=1,2,…….)
$\mathbf{L}_q$	q^{th} latent variable value vector
m	Forecasting Horizon
M, **P**	Loading Matrices
$\mathbf{m}_a$	Regression weights vector of component a
$\mathbf{m}_i$	**X** Weights of i^{th} PLS component
n	Forecast Origin
N	Number of competitive products in a market segment/ Samples
$\mathbf{p}_i$	Loadings of i^{th} PLS component

P	Price
$\mathbf{p}_a$	Regression loadings loading vector of component a
Q^2	Goodness of Prediction
R^2	Goodness of Fit
SS	Error Sum of Squares
$\mathbf{T}, \mathbf{U}$	Score Matrices
$\mathbf{t}_i$	**X** Scores of i^{th} PLS component
$\mathbf{u}_i$	**Y** Scores of i^{th} PLS component
V	Value
V_0	Baseline Value
$\mathbf{w}_{ij}$	Path modeling outer weight between i^{th} manifest variable and j^{th} latent variable
$\mathbf{X}$	Predictor Variables/Product Attribute Level
$\mathbf{x}_{ij}$	Regression modeling, i^{th} observation j^{th} predictor value
$\mathbf{Y}$	Response Variables/CRV
$\mathbf{y}_g$	Regression modeling g^{th} observation of response variable y
$\mathbf{z}_{gh}$	Path modeling g^{th} manifest variable connected to h^{th} latent variable

1 INTRODUCTION

1.1 Background

Largely globalised markets and constantly changing consumer demand behaviours are major challenges faced by today's manufactures. Year by year competition to survive in this dynamic market is getting intensive with the inclusion of new players, rapid innovations and improving technologies. Winners are the firms introducing the right products to the right markets at the right time.

In order to accomplish this challenging mission a streamlined process is needed to strategically plan and realize products. A manufacturer needs to plan product offerings strategically to maximize market shares and long-term revenues. Therefore, accurately forecasting the future market scenarios, and designing products to satisfy future customer preferences are the essential tasks to achieve these objectives.

Most of the leading products from respective market segments are strategically designed and placed products. Netbook, the ultra-light notebook, is a good example of a successful strategically planned product (Vance and Richtel 2009). Netbook was first introduced by product designers of a Taiwanese computer manufacturer in 2007. Their competitors were competing with each other to introduce high performance and expensive notebooks at that time. The Taiwanese manufacturing firm wisely predicted future demand for a low cost and high mobility device, which can tap in to the cloud computing resources, and started to develop a notebook with a new concept.

The Netbook design and development team timely identified and targeted the potential third world market boom, due to the craving for IT literacy. They recognized the impact of the One Laptop per Child initiative and emerging new class of specifically designed notebooks to cater third world customer needs. Since available notebooks did not address the demand for a low cost and low power consuming device, they prioritized these two attributes.

Netbook created a new product market segment, and its sales was accounted for 19% of total notebook sales in just one year from the introduction[1]. Strategically planned products, as described in the inspiring story of the Netbook, will ensure the market penetration and survival in the highly competitive market segments. Furthermore, in some instances, they would be able to create new market segments with whole new opportunities. After the success story of the Netbook manufacturer, it is better to take a look at the other end of the spectrum.

The current market status of US automakers can be taken as an example for the consequences of strategic insight lapses. Misled by incorrect future auto market predictions, US automakers keep on producing bigger and fuel consuming vehicles. Also, longer restyling cycles made their product lines stagnated. They were not prepared and agile enough to face the market shift towards smaller and fuel efficient automobiles, caused by the sky rocketing fuel price trend started from 2004. Their fuel efficient smaller car designs were inferior to the Asian and European designs due to unpaid attention over decades.

US automakers' competitors for their home market, European and Asian automakers, prepared to deliver green, fuel efficient automobiles to meet the future high oil prices and tight environmental regulations. Appropriately, the European and Asian manufacturers were rewarded for their strategic insights and years of research and development efforts with remarkable market share growths in the US auto market. According to a study done by Earth Times[2], US automobile manufacturers lost their market share of 73% in 1996 to 47% in 2008. The economic crisis together with their strategic lapses hit them hard in 2009, and they had to ask for a government bail-out to overcome a possible bankruptcy.

The success and failure stories covered earlier shows the significance of strategic product planning to survive the intensive competition of today’s technological product markets. Especially, in technologically saturated, well established market segments, customer driven

[1] https://mr.pricegrabber.com [2] http://www.earthtimes.org

design is the best strategic approach for the success. Using the right mix of product attributes to address the dynamic customer preferences, is the way to win the competition in those markets. Traditional design theory and techniques such as QFD (Quality Function Deployment) (Akao 1994), Design for Manufacture (DFM) (Boothroyd et al. 1994), Robust Design (Taguchi 1993), and Axiomatic Design (Suh 1999) are not sufficient to encounter today's challenges.

Industry needs more potent, a new breed of methods to handle the dynamic nature of the market, which is not addressed by the existing design tools. Especially, a strategic framework is needed for the design decision support, in order to understand time variant customer preferences and to incorporate them in the Product Design and Development (PDD) process. This novel framework should be able to bridge the gap between marketing and engineering by providing much needed strategic insights to the design decision makers.

Currently, "design for market systems" is becoming one of the leading topics in the domain of Design Theory and Methodology (DTM). The research study presented in this thesis is aimed at extending the earlier mentioned topic by incorporating the dynamic nature of the technological product markets to the front-end PDD decision making process. The final outcome of the research study presented in this thesis is a scientifically sound, Strategic Decision Support Framework, which can be used in the front-end product concept screening process. It can be used to empower the design decision makers, in order to screen out the best product concepts to efficiently address the future customer requirements.

1.2 Motivation

In customer driven product design approach, identification of customer requirements is the foremost important task. In this approach, the product concepts are characterized based on the customer requirements. Therefore, the product developers can raise one critical question, "Do we use the right set of customer requirements for the product development?" to assess the success of the product in the market. This is a tough question to provide an answer.

PDD process usually requires the time range of several months to many years depending on product types and development levels. The product development task can be a software redesign, part or sub-system redesign, and design innovation. In rapidly changing market places, the customer requirements used for the design decision-making may be easily outdated at the product launch time (Monczka et al. 2009; Tripas 2008). Therefore, products with longer PDD cycle times are the most affected group of products by the dynamic nature of the customer preferences.

Product attribute levels or the magnitudes of the product characteristics can be identified as the main factors influencing technological product performances at the market, such as values given by the customers, demands and profits (Nicholson and Snyder 2008; Louviere et al. 2000). Therefore, the product attribute levels are used as decision variables, for the front-end decision making process, inside technological product manufacturing firms. However, existing design decision support methods do not consider the dynamic nature of the customer preferences. A strategic decision support framework can be used to fill this gap by incorporating accurate predictions of future customer preferences with the PDD process. A strategically planned product will ensure the market penetration and higher levels of market performances with the desired product attribute levels, accurately addressing the future customer preference.

Understanding the time variant behaviour and accurately predicting the dynamic customer preferences play major roles in strategic product planning. Currently, industrial firms perform this important mission in an ad-hoc manner. Most of the design selection decisions are taken according to "gut feelings" of experienced industrial practitioners (Khan 2002). Therefore, the industry is in need of a scientifically sound Strategic Decision Support Framework (SDSF) for the early stage of PDD.

The early stage of PDD is critical to the success of a product, due to the committed manufacturing costs and exponentially increasing design change costs along the development process (Ulrich and Eppinger 2000; Hazelrigg 2003; Liu et al. 2008). Therefore, the best conceptual designs should be selected at this stage, before incurring further costs along the design the process. This early stage conceptual design screening process is called as the front-end product concept screening (Wassenaar et al. 2003; Withanage et al. 2012), from here onwards.

A scientifically sound Strategic Decision Support Framework will enhance the current PDD process by providing a basis for the front-end design decision making, in this important stage of the product life cycle. The proposed Strategic Decision Support Framework can minimize the waste of resources on inefficient product concepts, by identifying and screening them at the early product design stages. Therefore, manufacturing firms, customers and the whole society will be benefitted by the proposed Strategic Decision Support Framework.

1.3 Research Objectives

In the front-end conceptual design phase, many product concepts are generated by the product developers. Therefore, selecting the best product concept at this stage is critical to the success of a product at market, and to minimize the waste of resources as explained earlier.

The major objective of this research study is formulated as follows to enhance this important front-end design decision making task.

Research Objective

To formulate a framework to support the strategic decision making at the front-end concept screening phase

There are many challenges to overcome before achieving the major objective. Firstly, a metric for level of customer satisfaction is needed as the basis for the decision-making. Secondly, the relationship between the level of customer satisfaction and the product attribute levels is needed to be estimated. This relationship can be used to obtain the level of customer satisfaction generated by product concepts. These satisfaction levels will be used for the product concept screening process.

Thirdly, the dynamic nature of the product attributes and customer satisfaction relationship is needed to be captured and incorporated into the proposed framework to make it a "strategic" framework. This will enable an accurate replication of the dynamic market systems to support the front-end product concept screening with accurate predictions of the future market scenarios. These three important intermediate steps in achieving the main objective are considered as the sub-objectives of the research study. After setting the goals by formulating the objectives, the bounds of the research study are defined in the following section.

1.4 Scope

The targeted product group for this novel framework is technological products, and the underlying main theme of the research study is the customer driven design approach. Mainly, the definition of a product as an attribute bundle is used in this research study to provide the solutions in the context of customer driven design. In technological product markets, product attributes are considered as the main decision variables, which influence the customer satisfaction, as explained earlier. It is the rationale behind targeting this selected product group in the proposed approach.

The customer driven design approach is more important for products competing in technologically saturated, well established market segments. Especially, products from those market segments with longer concept-to-customer cycle times can suffer a lot, due to the dynamic nature of the market behaviour. Hence, within the group of technological products, a special attention is given to the products with longer concept-to-customer cycles times.

The proposed Strategic Decision Support Framework is intended to implement at the front-end concept screening phase of the technological PDD process. Hence, currently used product development methodologies are important topics for understanding the background and for identifying research gaps. In addition, measuring of the customer satisfaction and time variant modeling of the relationship between the level of satisfaction and product attribute levels are identified as the important topics to achieve the research objectives. These important topics are covered in the literature review presented in the next chapter.

The thesis mainly consists of two sections. The first section of the thesis, Chapters 1-3, provides the foundation for the research study. The thesis starts with the background, motivations, research objectives, and the research scope to clearly define the boundaries of the literature review. Chapter 2 consists of the literature review and the research gap analysis. The research questions and hypotheses are presented in Chapter 3. The outcomes of the research study are presented in Chapters 4-7.

A meta-model for the product value-attribute relationship is introduced with a robust Partial Least Squares Regression (PLSR) modeling method in Chapter 4. In Chapter 5, a novel dynamic PLSR modeling method is introduced to formulate the dynamic product value-attribute relationship. This dynamic product value-attribute relationship is extended to the dynamic product value-characteristics modeling in Chapter 6 by using a novel dynamic Partial Least Squares Path Modeling (PLSPM) method. The thesis concludes with the overall contributions, limitations and proposed future works, which are given in Chapter 7.

2 LITERATURE REVIEW

2.1 Product Design and Development (PDD)

A broad overview of the PDD research community and their activities presented at the forefront of the literature review, before narrowing down to the areas of interest as pointed out in the research scope. This section briefly reviews the profiles and objectives of the various research communities working on PDD related topics.

The review paper of Kirshnan and Ulrich (2001) summarizes the different perspectives of marketing, organizations, engineering and operation management research communities on PDD. In the marketing domain, a product is considered as a bundle of attributes, and market shares and consumer utility are used as the main performance metrics. In addition, use of consumer utility as a function of product attribute levels can be identified as the dominant representational paradigm for the level of customer satisfaction generated by a product. .

On the other hand, researchers from the engineering domain are more focused on technical performances and cost of a product. However, this paper was published in 2001 and the engineering design community has broadened its scope of PDD activities by conducting more interdisciplinary research studies. Now, there are research studies (Wassenar et al. 2003; Wassenar et al. 2005, Hoyle et al. 2010) extending the earlier perspectives by including marketing related activities inside the engineering design. Simply, they can be taken as the hybrids of marketing and engineering approaches.

Due to the hierarchy of activities in the PDD process, the level of abstract of the PDD research studies depends on the scope of researchers. As an example, determinants of the project outcomes at aggregate organizational levels are the main concerns of the organizational academic community (Brown and Eisenhardt 1995). Engineering and marketing community are working at more detailed levels of abstraction to provide solution to product design problems, which are encountered by product developers or market researchers at individual levels. Finger and Dixon (Finger and Dixon 1989a; Finger and Dixon 1989b) papers summarize research studies from the engineering domain, and Mahajan and Winds (1992) paper summarizes research studies from the marketing domain, in the mainstream PDD literature. These two research papers can be used to identify the leading works and to get more in depth understanding about the topics covered in respective areas.

In the proposed Strategic Decision Support Framework, strengths of marketing related methods can be used to enhance the engineering related PDD activities. In this novel framework, customer satisfaction is proposed to use as the design objective of the product concept screening process. Customer satisfaction is a typical performance metric in marketing, which is indirectly measured using the value or the utility of a product. The product concept screening is a task principally done by the design engineers at the front-end PDD phases. Usually, the product concept screening process is placed in-between the phases of system-level and detailed design (Ulrich and Eppinger 2000), as depicted in the generic PDD process (see Figure 2-1).

The front-end PDD activities, initial planning and concept development tasks, are shared by the marketing and engineering divisions (see Figure 2-1). The engineering division takes charge of the PDD process from the stage of system level design to the production ramp–up. After the production ramp-up, the marketing division is taking care of sales. Finally, it gives the essential feedback of the customers to the designers in the engineering division. This feedback, feed forward system ensures satisfaction of customer needs (Ulrich and Eppinger 2000).

Product Life-cycle Management (PLM) is a relatively new paradigm in the domain of product design. It is defined as “a strategic business approach for the effective management and use of corporate intellectual capital” (Amman 2002). Product Life-cycle Management integrates and optimizes the activities from product initialization to product retirement. The main objective of Product Life-cycle Management is boosting innovation in manufacturing to face the global level competition faced by manufacturing organizations (Amman 2002). In this research study priority is given to the front-end product concept screening, a small segment of activities, compared to the broad range of activities entailed with the Product Life-cycle Management.

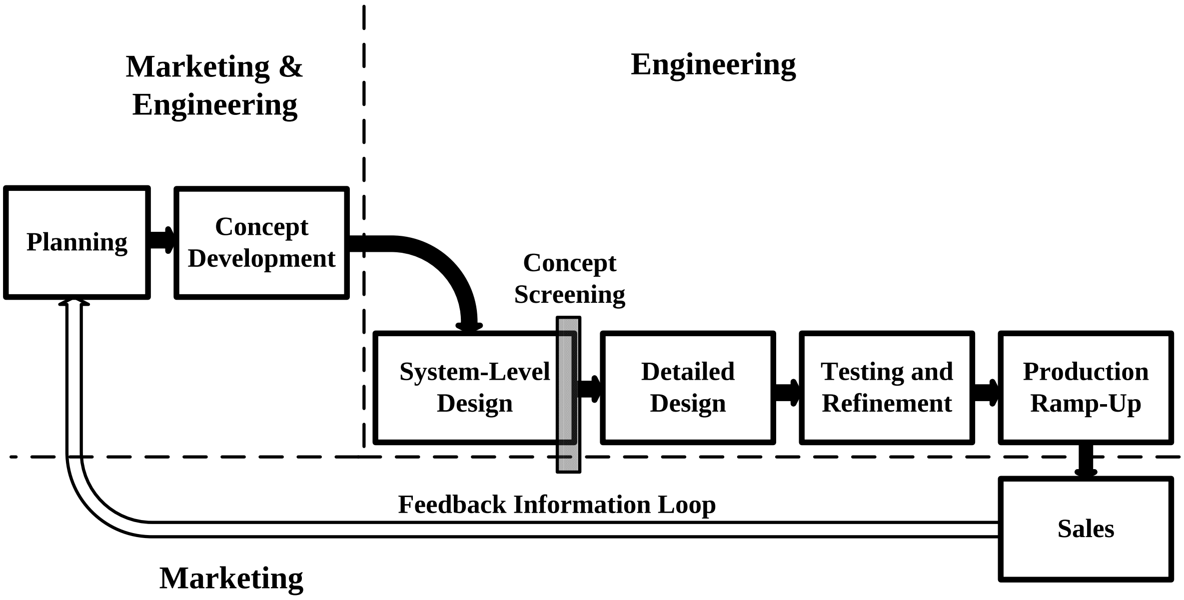

Figure 2-1 Product Design and Development (PDD) process

Front-end of the PDD process is the ideal phase to implement the Strategic Decision Support Framework, as stressed in Section 1.2. Integration of customer preference to the initial PDD process is the basic idea behind the customer driven design. In addition, exponentially increasing cost of design changes after the phase of concept development makes it more important.

The rest of the literature review is presented in a structured manner to identify the challenges, to present the potential existing approaches or solutions, and to pinpoint the research gaps in need of novel methodologies. Currently used techniques and methodologies are investigated in the following section to identify challenges in the front-end PDD activities and design decision support methods. The next two sections present the potential candidates and the research gaps in existing methods, which will be eventually used to formulate the research questions in Chapter 3.

2.2 Front-End Product Design and Development (PDD) Activities and Design Decision Support Methods

The proposed Strategic Decision Support Framework is aimed at the design decision making shared by the PDD marketing and engineering domains. In this section of the literature review, the PDD activities related to the main objective of the research and existing decision support methods are critically evaluated to find the research gaps.

Product planning and product optimization are multidisciplinary PDD activities, which can be taken as interceptions of marketing and engineering domains. Product planning can be defined as the process of identifying product attributes/features important to the market segment and generating the product concepts. Product optimization can be defined as optimizing the firm's objectives by adjusting the product attributes. The mainstream product development methodologies (Wassenaar et al. 2003; van de Poel 2007; Cook and Wu 2001) are used as the decision support tools in these two activities up to various extents. Therefore, the mainstream product development methodologies are investigated in a separate subsection to identify the area in need of improvements.

On the other hand, customer preference/choice elicitation (Green and Rao 1971; Louviere et al. 2000) can be taken as an activity of the marketing domain. In product development methodologies, preference/choice analyses are used to estimate the product values, utilities, or market shares. Ultimately, these product performance measurements are used as the design objectives of the product planning and optimization processes. These methods are investigated in a dedicated subsection, due to their dominant role as PDD decision support methods.

New product demand forecasting is another important activity unique to the marketing domain (Makridakis 1996; Rabikar and Yoshi 1990). It deals with product concepts and the market dynamics, which are characteristics expected from the Strategic Decision Support

Framework. Therefore, it can be recognized as an activity closely related to the main objective of the research study. Forecasting techniques are the tools used in this activity to get the future market predictions. Hence, the new product demand forecasting methods are investigated in a subsection, while paying special attention to the quantitative forecasting techniques.

The following three supporting subsections focused on the product development methodologies, customer preference/choice modeling and new product forecasting, which are identified as the areas of interest from the marketing and engineering PDD domains.

Product Development Methodologies

The mainstream product development methodologies mainly support two key activities, product planning and product optimization, up to various extents. These activities are conducted according to long or short term goals of the firm. Objectives such as customer satisfaction, market shares, profit, etc. can be used for this process. In addition to those objectives, the design decision makers should think about the technological capabilities and other constraints acting on the firm's design and manufacturing processes, while planning and optimizing a product (Wassenaar et al. 2003; Wassenaar et al. 2005; Li and Azarm 2000).

In current industrial settings product planning and optimization activities are mainly done at the front-end PDD phases. Especially in the case of product optimization, availability of cutting edge simulation software and computational resources has made it more front-end bound, compared to the earlier times. In the context of customer driven design, the main objective of this activity is to maximize the customer satisfaction by accurately addressing customer requirements. It is attained by fine tuning the mix and the levels of product attributes, within the feasibility region in the product attribute space.

Product development methodologies, under the category of customer driven design approach, can be further categorized into different branches. They can be categorized by the theoretical techniques used to integrate the customer preferences/choices into the product development process. Most of the product development methodologies are based on choice modeling (Wassenaar and Chen 2003), multi-attribute utility (Thurston 2001) and value driven design (Donndelinger and Cook 1997). According to the new design paradigm called Decision Based Design (DBD) (Hazelrigg 1998), Bayesian choice modeling is the recommended technique to integrate customer preference into the product development process. However, multi-attribute utility and value driven design are also used in the DBD approach.

Quality Function Deployment (QFD) is the most popular customer driven product development methodology widely used in the industry (van de Poel 2007). The DBD community recognized QFD as a useful methodology for industrial applications; however, it is not accepted as a theoretically sound method by them (Wassenaar and Chen 2003). Currently, DBD framework proposed by Wassenaar and Chen (2003), based on discrete choice analysis, is considered as the representative framework for DBD approach in the design community. Its popularity in the design community and alignment with the Hazelrigg (1998), the ground breaking paper, has made it the leading framework of DBD. Also, multi-attribute utility theory and value driven design approach can be found in some DBD related publications.

The notion of product value in value driven design (Donndelinger and Cook 1997) and stakeholders' utility in multi-attribute utility are similar to each other. The main difference is the techniques used to elicit the value or utility in these approaches. In value driven design micro-economic demand price analysis is used to estimate the values of products, in contrast to the stake holder assessments used in multi-attribute utility. Independent from the DBD research community, value driven design had grown as a separate framework. Especially, the research group of Cook at al. contributed with many papers on this topic. Thus, QFD product development methodology, DBD and value driven design product development frameworks are further explored in the following subsections.

Quality Function Deployment (QFD) Product Development Methodology: QFD is a Japanese quality management method developed in late 1960s (Akao 1990; van de Poel 2007). Success of Japanese industry during 1970s prompted USA and European countries to adapt the quality methods developed in Japan. In current industrial settings, QFD is one of the most widely used product development methods (van de Poel 2007).

The main objectives of QFD are to improve quality of the products, reduce development and other pre-production costs, increase organization capabilities, and ultimately make industry more competitive. Basically, QFD is considered as a tool for customer driven product development to better address customer needs (Womack et al. 1990). However, some papers (Hauser and Clausing 1988; Bergquist and Abesekera 1996) claimed that the main objective of QFD is to develop products, instead of achieving the above mentioned business goals.

Translating customer needs into engineering specifications of a product is the key function of QFD. It uses the “voice of the customers” to elicit the customer preferences, in order to plan the product offerings accordingly. In QFD, most important and promising engineering characteristics are screened in a systematic and quantitative approach, using customer demands and engineering specification relationships. Then, target values are set for these promising attributes for the improvement. This approach ensures the enhancement of the effective competitiveness of products, by the means of the improved customer satisfaction (Fung el al. 2003). House of Quality (HOQ) is the most important element in QFD, which is used to integrate the preferences of customers and technical specifications of products (van de Poel 2007).

House of Quality translates customer demands “WHAT” to technical specifications “HOW” using a relationship matrix. A chain of House of Quality matrices is used from the system to component level design, in order to reach design parameters influencing system performance. Technical specification at the system level considered as “WHATS” in second level, and product components or components specifications are considered as “HOWS”. Using this mechanism, top level customer needs are translated into the bottom level technical specifications.

QFD is an attractive solution for product designers due to its simplicity. However, it has got some limitations and theoretically weak points. It lacks the ability of developing entirely new product designs, due to customers' inability to raise their voice about products new to them. Also, QFD may include errors in representing customer demands since it uses a linear additive value function. The preference aggregation, which is done in the "voice of the customers" phase, raises questions about the theoretical validity of QFD (van de Poel 2007). Also, the trade-offs between multiple demands may not be accurately tracked. However, Maltzler and Hinterhuber (1998) suggested combining Kano's model with customer demands, as a solution to overcome this problem.

QFD, as a ground-breaking tool of customer driven design, totally change the perspectives on the conventional PDD process. It replaced the short term profit goals of the organizations by the more sustainable objective of customer satisfaction. Thus, QFD is important to this research study, due to its dominant place in early product development methodologies. Especially, it is important as a forerunner of the customer driven product design approach. Nevertheless, QFD analysis is limited to the current market scenarios, and it lacks the prediction ability of future market scenarios and time variant market behaviours.

Decision Based Design (DBD) Product Development Frameworks: In late 1990s engineering research community recognized the importance of decision making in engineering design. Furthermore, they saw that fundamental construct in engineering design is decisions. This movement finally cemented the Decision Based Design, a new perspective in engineering design. The major concern of Decision Based Design is decisions made by designers during the design process. The main concept behind Decision Based Design is taking engineering design as a decision making process, in contrast to the popular problem solving approach.

Decision Based Design approach is based on the decision theory, the roots of which go back to early 1930s. Fishburn (1989) has attributed the success of modern formats of decision analysis to their roots, expected utility theories of Ramsey (1931), von Neumann and Morgenstern (1944), and Savage (1954). A descriptive work about the decision process can be found in McFadden's paper (1999). Inspired by the decision theory, Hazelrigg (1998) came out with a framework for design decision making.

In his paper, Hazelrigg (1998) emphasizes the importance of taking “maximizing profit to the company” as the corporate preference. Every decision should be taken in order to achieve this single objective. He has highlighted the necessity of considering uncertainties in every decision making situation. In his 1996 paper on Arrow's impossibility theorem (Arrow 1950; Blau 1957) and its implications on optimal design, Hazelrigg suggested Bayesian choice modeling as the answer for integrating customer preferences inside a product development framework. According to this framework, individual customer choices can be aggregated in to product demands, and demands can be written as a function of prices and level of attributes (Hazelrigg 1996a; Hazelrigg 1996b).

The Decision Based Design product development approach (Thurston 2001; Wassenaar et al. 2003) was founded on the framework suggested by Hazellrigg. The framework proposed by the research group of Chen et al. (Wassenaar et al. 2003), based on Hazellrigg (1996a; 1996b), is considered as the benchmark product development frameworks from the Decision Based Design community. This can be justified by the recognition received by their work from the Decision Based Design community and the PDD community in general, as explained earlier. In addition, this framework covers all the design activities from the product concept generation, product optimization and front-end product concept screening processes. However, there are other Decision Based Design frameworks proposed using multi-attribute utility (Thurston 2006), demand modeling (Cook 2006) and preference modeling (See et al. 2006). The above references are taken from the book titled "Decision Making in Engineering Design", which is published by the Decision Based Design community. It contains more articles about alternative frameworks and views on Decision Based Design.

The Decision Based Design framework proposed by Hazellrigg (1996a; 1996b) and Chen et al. (Wassenaar et al. 2003) is based on Bayesian choice modeling with the objective of maximization of the organizational profit. Discrete Choice Analysis (DCA) and Conjoint Analysis (CA) are used to find market shares of conceptual products in this framework. These market shares are used to calculate demands, and the Net Present Value (NPV) of the profit. In popular publications (Wassenar et al. 2005; Li and Azarm 2000), the Net Present Value of the profit is used as the design objective. In the Decision Based Design papers based on multi-attribute utility theory, an expert's utility function value is used as the main objective (Thurston 2001). Thus, the accurate representation of customer preferences or requirements is not the main objective of these methods.

In the Decision Based Design literature, researchers (Wassenar et al. 2005; Li and Azarm 2000) have depicted market shares as a time variant function of attribute levels and prices. Anyway, the effect of time variant market systems is not accounted for in their presented case studies. This can be recognized as a major setback of Decision Based Design in evaluating and generating futuristic design concepts. The effects of customer preference shifts can make the decisions which are taken at the initial design stages questionable in latter stages. Especially, these effects can be amplified on products with longer design cycle times in volatile technological markets.

Value Driven Product Design Product Development Framework: Value Driven Product Design is the least used framework, out of the three product development methodologies and frameworks presented in the literature review. In Value Driven Product Design approach, design decision makers are trying to maximize the objective function of customer value generated by levels of product attributes (Cook and Gill 1992; Cook and Kolli 1994).

In the system level, the concept of Value Driven Product Design is analogous to the Multi-Attribute Utility Theory. As explained earlier, the main difference is the estimation process of the design objectives used in these analyses. Product value, estimated from a micro-economic analysis, is used in the Value Driven Design; whereas, the utility, estimated by stakeholder assessments, is used in the Multi-Attribute Utility method (Cook and Wissmann 2007; Thevenot et al. 2007; Fernández et al. 2005; Marston and Mistree 1998).

S-Model or Simple Market Model (Cook and Gill 1992; Cook and Kolli 1994; Cook and Wu 2001; Cook and Wissmann 2007; Donndelinger and Cook 1997; Downen et al. 2005)is the basis of the value driven design approach. S-Model was derived by Cook following the traditional micro economic theory, where demand of a product is given as a consumers' value function, the product price and constraints on consumer income (Nicholson and Snyder 2008). Customer Revealed Value (CRV), the product value metric used in the Value Driven Design approach can be easily estimated using the S-Model of the product market segment (Cook and Kolli 1994; Cook and Wu 2001, Donndelinger and Cook 1997).

CRV is a product of a micro economic, demand-price analysis of the market segment. In addition, it is a useful metric of the perceived value of products, which has been validated in many industrial case studies including the automobile and air plane manufacturing industries (Cook and Kolli 1994; Cook and Wu 2001; Donndelinger and Cook 1997; Downen et al. 2005). According to Cook and Kolli (1994), the demand of a product, D is determined by Equation 2.1, where K is the partial derivative of demand with price, V is value, P is price, and N is number of competitive products in a market segment.

$$D_i = K\left\{(V_i - P_i) - \frac{1}{N}\sum_{j \neq i}(V_j - P_j)\right\} \quad 2.1$$

The coefficient *K* can be obtained using Equation 2.2, where E_1 is ratio of price elasticity, $\overline{D}$ is average demand, and $\overline{P}$ is average price.

$$K = E_1 \frac{\overline{D}}{\overline{P}} \quad 2.2$$

The ratio of the price elasticity *is* given by $E_1 = NE_2$, where E_2 is the price elasticity of the market segment. This implies a situation, where the prices of all products in a market segment are changed by the same amount while keeping the value unchanged. The set of simultaneous equations of *N* competing products are solved to obtain the CRV (given by Equation 2.3) of a product in units of dollars, using the total demand of the market segment, D_T.

$$CRV_i = \frac{N}{(N+1)K}(D_i + D_T) + P_i \quad 2.3$$

CRV represents the perceived value of a product, and provides an index to differentiate products using the value instead of using the sales or prices. In Cook's articles (Donndelinger and Cook 1997) he showed that the revealed value differences (base line or average value from market segment subtracted from the revealed value of the product) obtained from demand price analysis is analogous to value differences obtained from multiple attribute analysis.

Using this relationship, product value-attribute relationship, the relationship between product attribute levels and the overall product value, is estimated in the value driven product design approach. The value curve method, which is used to model the value of the product, corresponds to a product attribute level, is depicted in Figure 2-3. A value curve can be modelled according to the Equation 2-4, where γ is the exponent weight of the attribute. The exponent weight is equal to the time fraction of the attribute, up to which amount the attribute is influential during the use of product.

$$v(g) = \frac{V(g)}{V_0} = \left\{ \frac{[g_C - g_I]^2 - [g - g_I]^2}{[g_C - g_I]^2 - [g_0 - g_I]^2} \right\}^{\gamma} \qquad 2.4$$

Therefore, product value generated by a product attribute can be given as a function of the product attribute level (g), base line specification (g_0), critical specification (g_C) and ideal specification (g_I). The base line specification is the mean attribute level in the product market segment, whereas critical and ideal refer to the attribute levels correspond to zero and maximum levels of values (see Figure 2-2).

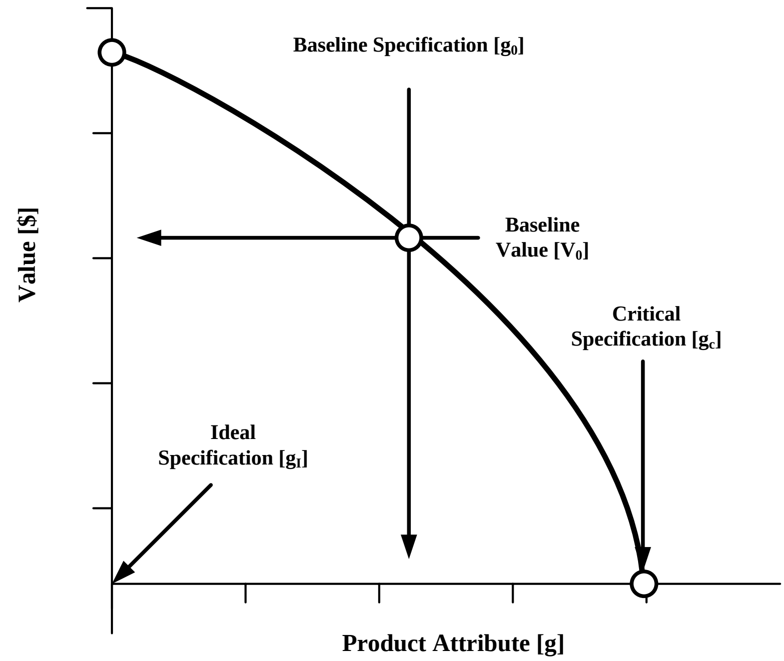

Figure 2-2 Value curves (Donndelinger and Cook 1997)

The overall value of the product is given by Equation 2-5. Multiplication of each and every *v(*g*)* provides this heuristic expression of the overall value. The symbol ΔV_{opt} is used here to represent the salvageable options and other attribute values, which have not got well defined critical specification (g_c, see Figure 2-2).

$$V_i = V_0 v(g_1) v(g_2) v(g_3) v(g_4) \ldots\ldots. v(g_j) + \Delta V_{opt} \qquad 2.5$$

This equation can be rearranged as given in Equation 2.6, where k is the number of product attributes.

$$V = V_0 \prod_{i=1}^{k} v(g_i) + \Delta V_{opt} \qquad 2.6$$

The value-attribute relationship of a market segment can be obtained by substituting the CRV estimation from Equation 2.3 to right hand side value (V) of Equation 2.6. Thus, γ can be estimated using a least squares estimation. The CRVs of product concepts can be obtained using this relationship.

The main advantage of this product development approach is the readily available data for the value estimation, compared with cost and time consuming surveys needed in Discrete Choice Analysis, Conjoint Analysis and other popular methods. The assumptions of a linear demand function in S-Model and clearly defined ideal and critical product specification levels (see Figure 2-2) are the drawbacks of this approach. In addition, time variant modeling applications are not available in the value driven product design literature.

Customer Preference/Choice Modeling

The mainstream marketing, product value and utility modeling methods can be categorized under either the preference modeling approach or the choice modeling approach. The preference modeling approach is used to explore the underlying preference structures, and the choice modeling is mainly used for the aggregated choice or market share predictions. In addition, the main preference and choice modeling approaches can be categorizes according to the type of data used for the analyses.

Data collected by surveys, focus groups and interviews is used in Stated Preference (SP) methods. Revealed Preference (RP) methods are based on observations of real life behaviours.

Simply, Stated Preference analyses are based on what customers are saying, and Revealed Preference analyses are based on what they actually do. However, each Stated Preference and Revealed Preference approaches are coming with advantages as well as disadvantages. The best way to extract customer preference is using them together, which is called the method of data enrichment (Louviere et al. 2000).

Revealed Preference methods are bounded by the current technological barriers. Hence, Revealed Preference methods are only used to optimize product parameters in the short term product development tasks. Stated Preference methods are the only available way to assess innovative product or service configurations, which surpass the current technological bounds. In the Innovation Driven Product Design Approach, Stated Preference methods are used to check customers' reaction to completely new product concepts, new configurations and improvements of existing designs.

There is a disagreement between the two groups (i.e., Stated Preference and Revealed Preference) in economic research community, over the issue of the most effective approach. Horsky et al. (2004) is one of the studies tried to explore this issue. The article contains a detailed discussion about empirical studies of Kraus (1995), Petty and Krosnic (1995), Ratner and Miller (2001), where the inconsistency of actual and stated choices is observed. In their research study results, they have observed overweighting of intangible attributes resulted by Stated Preference methods. A comparison of Stated Preference and Revealed Preference methods are given in Table 2-1.

The most notable missing point in current Revealed Preference and Stated Preference research is the effect of time. Currently, Stated Preference methods are the only way to evaluate futuristic concepts, and more reliable Revealed Preference data cannot be used in this important task. There is not any time variant preference method presented in the main stream PDD literature.

Table 2-1 Revealed Preference methods versus Stated Preference methods

Characteristics	Revealed Preference	Stated Preference
Data collection	Sales, Customer database, Product database Real market observation plus product specification (optionally customer characteristics) (Berry et al. 1995; Ben-Akiwa et al. 2002; Donndelinger and Cook 1997)	Questionnaires, Focus groups, Interviews Data collected through a preference elicitation method (Green and Rao 1971; Louviere et al. 2000; Wassenar et al. 2005)
Reliability of the data (Horsky et al. 2004; Kraus 1995; Ratner and Miller 2001; Petty and Krosnic 1995)	Good	Questionable
Alternatives considered in the study (Louviere et al. 2000)	Currently available alternatives	Currently available alternatives plus futuristic alternatives
Cost of data collection (Donndelinger and Cook 1997; Downen et al. 2005)	Cost of data transaction	Expenses involved in designing to conducting of a survey
Availability of data (Donndelinger and Cook 1997; Downen et al. 2005)	High availability for insiders	Have to conduct a survey to get data
Applications (Louviere et al. 2000)	Product improvements using existing technology	New concept exploration and product improvements

The most popular techniques used for the preference elicitation and choice modeling in PDD activities are Conjoint Analysis (CA) and Discrete Choice Analysis (DCA). In the following subsections, these two techniques are investigated to find the limitations.

Conjoint Analysis (CA): Conjoint Analysis is a widely used method in marketing research to model consumer preferences among multi-attribute alternatives. It is founded on the seminal work of Luce and Tukey (1964), and it became a mainstream marketing research tool with the Green's and Rao's (1971) customer oriented paper. The main objective of Conjoint Analysis is to identify important attributes of a product or a service using survey respondent ratings (Weerahandi and Moitra 1995). Currently, “Conjoint Analysis” term is used for all disaggregating methods that estimate the structure of consumer’s preferences (Green and Rao 1971; Green and Srinivasan 1978).

Conjoint Analysis is based on mathematical psychology, where the main focus is on conditions to check the study of scaled independent and dependent variables is feasible. Also, the order of the joint effects between independent variables, and a pre-specified composition rule are important factors considered in the analyses. In addition, Conjoint Analysis is closely related to the modeling of clinical judgements and functional measurements in applied psychology (Green and Srinivasan 1978).

Conjoint Analysis enables the quantification of judgemental data, which has been an age old quest of marketing researchers. The part-worth function approach in preference modeling is broadly used for this purpose, due to the easily interpretable graphical displays. The important steps of Conjoint Analysis are the data collection, stimulus set construction, and presentation of the analysis results. According to the number of attributes considered in the analysis, different approaches are used to model the preferences.

Full profile or concept evaluation approach is more important for PDD applications, since it can be used to evaluate many characteristics of the product at the same time. Most of the products have got more than one important characteristic, and the number of product characteristics is increasing with the complexity of the product. The full profile approach utilizes a complete set of factors in the analysis.

The major drawback of this approach is dissimilarity between real life situations and analysis setup, due to artificially increased number of choices in the analysis. This is called information overloading, and the number of factors should be restricted to overcome the overloading (Carrol and Green 1995; Green and Srinivasan 1990). In addition, the omission of time variant properties of preferences can be identified as a setback.

Discrete Choice Analysis (DCA): Discrete Choice Analysis (Louviere et al. 2000) focuses on accurate market choice predictions by using experimental replication of the market. Hence, the prediction ability of Discrete Choice Analysis is superior to Conjoint Analysis, and Discrete Choice Analysis is used in market share predictions.

Random Utility Modeling (RUM) approach (McFadden 2000; Ben-Akiwa et al. 2002) is the forerunner of the Discrete Choice Analysis method. The main difference between Random Utility Modeling and Discrete Choice Analysis is the type of data used in the analyses. Discrete Choice Analysis can be used with Revealed Preference and Stated Preference data. Basically, Random Utility Modeling is considered as a Revealed Preference data analysis method.

The Bayesian approach in choice modeling is promoted by Hazelrigg (Hazelrigg 1996b) as the solution to encounter Arrow's impossibility theorem. Currently, Discrete Choice Analysis is one of the leading methods used in Decision Based Design and other industrial applications. Many works published by Wei Chen, Wassenaar and their group (Wassenaar et al 2003; Wassenaar et al. 2005; Hoyle and Chen 2009) validated and prompted the importance of Discrete Choice Analysis for the Decision Based Design approach.

In the Decision Based Design application, Discrete Choice Analysis is used to capture the individual customer's choice behaviour by considering levels of attributes of competitive products (Hoyle and Wei-Chen 2009; Wassenar et al. 2005). In order to achieve this objective, the individual choice/utility generated is modelled as a function of product attributes and demographic attributes of the customer. Requirement of customers' demographic attributes is a drawback in situations where no database is kept, and when it is hard to conduct surveys.

An extended Bayesian Choice Modeling method is available in the PDD literature with higher level product characteristics (Hoyle et al. 2010), which represent the abstract, top level customer desires or perceptions. These higher level product characteristics are generated by the product attribute levels. In addition to the product and customer demographic data, a Latent Variable (LV) layer is added in these hierarchical Bayesian choice models. Also, these higher level characteristics are closer to the customers than the product attributes. As an example, customers are more sensitive to the overall engine performance of a car, compared with the individual product attribute levels such as horsepower, torque, displacement and fuel efficiency. However, these LVs are not directly measurable, and special estimation processes are needed to measure them.

The hierarchical model parameters are estimated using Maximum Likelihood Estimation (MLE) techniques, following the Structural Equation Modeling (SEM) approach (Kline 2011). The hierarchical Bayesian models are handicapped by assumptions of Maximum Likelihood Estimation techniques, regarding the joint distribution of variables and independence of observations (Vilares et al. 2010). The higher observation requirement, the high ratio needed between number of estimated parameters and observations, is another shortcoming of this method.

All Conjoint Analysis methods including Discrete Choice Analysis (used with Stated Preference data) are not providing entirely reliable outcomes, due to the difference between real life choices and stated choices. Also, Multicollinearity of variables can hamper the effectiveness of analyses due to the theoretical assumptions. Independence of product attributes is a basic assumption in Discrete Choice Analysis and Conjoint Analysis. This is a major drawback due to the highly correlated product attribute data in technological product markets. In addition, the absence of dynamic modeling methods is a shortcoming common to both categories.

New Product Demand Forecasting

The new product demand forecasting methods are important to this research, since they can provide insights about how marketing analyst are dealing with the new product concepts. Furthermore, the forecasting techniques used for this strategically important activity (Kahn 2002) can be utilized to incorporate dynamic market behaviour to the proposed framework. Therefore, the forecasting techniques used in this activity are reviewed in this sub section to find the most appropriate techniques to devise the proposed framework.

Basically, there are two types of new product demand forecasting techniques: the qualitative and quantitative methods (Kahn 2002). The popular qualitative type methods are Delphi Method and Jury of Executive Opinion, which are based on the "gut feelings" and the experiences of the decision makers (Kahn 2002; Downen et al. 2005). In qualitative type of methods, the forecasting errors can be increased, due to the errors in human decision making. Therefore, the main focus is given to the quantitative type methods, which are based on the standard statistical or numerical methods to generate the forecasts. In the new product demand forecasting process, casual and time series forecasting techniques are used to get the quantitative forecasts.

The causal or associative forecasting techniques are based on the assumption of the variable being forecasted is related to some other environmental variables (Reid and Sanders

2010). The earlier explained market research related preference/choice modeling methods are the best examples for the casual forecasting techniques. Regression Analysis is another widely used causal forecasting method (Reid and Sanders 2010; Hanke et al. 2001). Especially, in the technological forecasting domain Regression Analysis is used together with Data Envelopment Analysis (DEA) (Cook and Seiford 2009; Klimberg et al. 2005) to obtain the efficiency scores of comparable units and the production frontiers.

Also, Expert Systems (Liao 2005; Kandil et al. 2002) and Case Based Reasoning (McIntyre et al. 1994; Jo et al. 1997) methods can be recognized as more recent additions from the Artificial Intelligence (AI) research domain (Wang et al. 2009) to the casual forecasting approach. However, Artificial Neural Network (ANN), another AI based forecasting technique, can be used in time series forecasting approach, in addition to the casual forecasting approach. The main problems entailed with casual forecasting techniques are identification of the associative variables and the availability of the associative variable data (Reid and Sanders 2010).

Time series forecasting techniques represent the other branch of the quantitative forecasting techniques. The time series forecasting approach is based on the assumptions of sufficiency of the time series data to generate forecasts and the reappearance of past patterns in the future forecasts (Reid and Sanders 2010). Therefore, lookalike forecasting approach is needed to use with time series forecasting techniques with completely new and reconfigured products. In the lookalike forecasting approach, an existing product from the market segment is selected to get the historical demand observations, the primary requirement of time series forecasting techniques (Kahn 2002).

Exponential Smoothing, Moving Average (MA), and Auto Regressive (AR) techniques (De Gooijer and Hyndman 2006) are considered as the statistical time series forecasting methods. The forecasts of these techniques are controlled by the forecasting weights, which are obtained by minimizing the forecasting errors. However, there is a new breed of techniques such as ANN

(Zhang and Qi 2005; Kuo et al. 2001) and Grey Systems Theory (Hsu and Chen 2003; Akay and Atak 2007) based time series forecasting techniques.

Especially, ANN and Grey Systems theory are preferred over statistical time series forecasting methods to handle nonlinear problems (Kayacan et al. 2010). The main setbacks with ANN are its high training data requirements and the relatively long training period for generalization (Jo 2003). Interestingly, Grey Systems Theory is based on incomplete information as its name suggests (Liu et al. 2012), and it is considered as a method which can be used with minimum time series observations (Kayacan et al. 2010). However, the Grey system parameter are estimated via an Ordinary Least Square estimation process (Hsu and Chen 2003; Akay and Atak 2007).

The preference/choice modeling based casual forecasting techniques are limited to a single time frame. They are used to obtain the forecasts of the whole market segment assuming preferences are time invariant. In contrast to the whole market segment predictions of these methods, demand forecasts of one product can be obtained using time series forecasting methods. Time series forecasting methods have been combined with the choice modeling to obtain a dynamic choice model in a previous paper (Kim et al. 2005). This paper can be considered as a precursor study for the proposed Strategic Decision Support Framework. However, they have used DCA and projected the models to the future without considering the structural integrity of the model.

A novel dynamic model to represent the whole market segment can be formulated by combining a powerful multivariate analysis method with more clear structural properties, and a time series forecasting techniques. The inherent structural properties of the projected future models can be preserved by minimizing an error term consisting of forecasting errors and model structural errors. However, the back propagation weight estimation process of ANN (Zhang and Qi 2005; Kuo et al. 2001) and Ordinary Least Squares system parameter estimation process of Grey Systems Theory (Akay and Atak 2007; Hsu and Chen 2003; Kayacan et al. 2010) make them undesirable to combine with a multivariate analysis method.

In contrast to these two forecasting techniques, the statistical time series methods can be used to formulate the proposed dynamic model by minimizing the forecasting and model structural errors to estimate the optimal weights. Therefore, the strengths of multivariate analysis and time series forecasting can be exploited by combining them together to formulate a novel dynamic modeling method. Section 2.3 provides more discussions on the challenges and opportunities identified in the conducted background literature review, in order to formulate the proposed framework.

2.3 Product Design and Development (PDD) Decision Support Methods: Challenges and Opportunities

The challenges identified in the background literature review of the product development methodologies, revealed and stated preference/choice modeling methods and new product forecasting methods are summarized in this section. These challenges are clearly defined here, in order to identify the opportunities in the discipline of design theory and methodology to improve the front-end product concept screening process.

The preference/choice modeling methods are used as the decision support tools at the front-end product concept screening phase, in the mainstream product development methodologies (Hoyle and Wei-Chen 2009; Wassenaar et al. 2005; See et al. 2006; Li and Azram 2000). However, these modeling methods are limited to a single time frame, and as a result, customer preference changes with time are not represented in the product development methodologies. In other words, the mainstream product development methodologies are based on the unrealistic assumption of time invariant customer preferences. Especially, this unrealistic assumption can bring severe consequences in highly volatile technological product market segments (Monczka et al. 2009).

In addition, technological product developers are faced with the challenge of handling high dimensional data sets with few observations, which are infested with multicollinear predictor variables. Highly correlated technological product attributes are the root cause of this problem (Withanage et al. 2010b). Furthermore, this can be seen more severely in the Revealed Preference analysis methods. However, even in the Stated Preference analyses they have to be careful about the survey designs (Louviere et al. 2000) to avoid the multicollinearity. Therefore, variable screening methods are used to remove correlated variables in preference/choice analyses.

The mainstream preference/choice modeling methods are not equipped to handle the multicollinearity of variables, as explained earlier. Sometimes, important attribute data is unusable due to this problem. Out of the whole spectrum of attributes available, only few can be selected for the product value-attribute modeling. Also, combining attributes into one variable is another standard way to avoid this problem (Wassenar et al. 2005). Anyway, these approaches are not addressing the root cause of the problem. Hence, PDD needs a robust modeling method which can handle the multicollinearity of product attributes efficiently.

The Hierarchical Bayesian models provide more insights about market segments, by providing information about directly unmeasurable higher level product characteristics (Ben Akiwa et al. 2002; Hoyle et al. 2010). Unfortunately, they are more vulnerable to shortcomings of the design data. Currently, due to the high data requirements only few studies are available in PDD literature with limited variables (Hoyle et al. 2010).

The higher observation requirement (Kline 2011) of currently used Structural Equation Modeling (SEM) method is a big barrier to conduct a low cost Revealed Preference study. Especially, this is even tougher in situations where any survey or customer demographic data is not available. Practically, it is nearly impossible to collect customer demographic data due to the nature of some market segments. Stated and Revealed Preference studies with customer demographic data cost a lot of resources. On the other hand, the low number of observations is a challenge for the studies conducted without customer demographic data.

Endogeneity and heteroscedasticity (Cameron and Trivedi 2005) are the most important errors, which have to be considered in preference/choice modeling. Generally, endogeneity errors are occurred when predictor variables are correlated with the modeling error (Neter et al. 2004). This can happen when one correlated variable is screened out from the model, due to the limited available observations. Heteroscedastic errors can be occurred due to the nature of the data and inadequacy of the modeling parameters (Cameron and Trivedi 2005).

In the mainstream preference/choice modeling methods (Green and Rao 1971; Green and Srinivasan 1978; Louviere et al. 2000; Wassenaar et al 2003), product price is used as one the most important predictor variables. Anyway, there are so many problems entailed with this approach, because price is not a totally controllable variable, and price endogeneity can affect the model (Cameron and Trivedi 2005). A pure product value-attribute modeling method is the simplest way to avoid this problem. A separately estimated product value can be used with pure product attributes (excluding price), to find a pure product value-attribute relationship, while avoiding the price endogeneity (Donndelinger and Cook 1997; Downen et al. 2005). The value curves introduced in the Value Driven Design approach is an example for a pure product value-characteristic modeling method.

The value metric of the Value Driven Design approach, CRV, provides an opportunity to separate the product value estimation process and the product value-attribute relationship modeling process. On the other hand, the standard procedures and rigid model parameter estimation methods, such as Maximum Likelihood Estimation (Louviere et al. 2000), make the estimated preference/choice models (Green and Rao 1971; Green and Srinivasan 1978; Louviere et al. 2000; Wassenaar et al 2003) unrealistic in some situations. In contrast to these methods, CRV gives the flexibility to choose a modeling technique to overcome the multicollinearity and other shortcomings of the technological product market segment data sets.

In addition, CRV provides a pure product characteristic value equivalent to the perceived value of products (Donndelinger and Cook 1997). The product market customer behaviors are reflected in CRV estimations through the demand and price fluctuations. However, the multivariate analysis technique to estimate the product value-attribute relationship should be carefully selected, according to the nature of the product market segment data considered in the analysis.

Heteroscedastic errors are caused by uneven variances in the predictor variable space (Neter et al. 2004; Cameron and Trivedi 2005). In most of the statistical modeling methods, homoscedasticity is a basic assumption. Hence, violation of this assumption can cause the models theoretically and practically unreliable (Neter et al. 2004). Using transformed response variables for the model formulation is the most popular way to minimize the effect of heteroscedasticity. The weighted least square modeling approach is one example of an advanced, more effective way to deal with this error (Davidian and Carroll 1987; Neter et al. 2004; Box and Meyer 1986).

Multicollinearity of data, endogeneity, heteroscedasticity and high dimensional data with limited number of observations are the main challenges identified in this section. These shortcomings should be addressed with the modeling techniques and the modeling approach. Therefore, multivariate analysis methods including PLSR and PLSPM are explored in the next section to inspect the potential of them as preference modeling methods. The literature review is narrowed down to the multivariate analysis methods with well known structural properties. In addition, only the methods which are well known for the efficient handling of high dimensional and highly correlated data sets (Eriksson et al. 2006; Wold et al. 2001) are selected. Special attention is given to the PLSPM method; due to its ability to model the "latent" or higher level characteristics.

The main objective of research can be only achieved through a dynamic modeling method, which can predict the future preferences or future market scenarios. Kim et al. (2005)

used time series forecasting algorithms to project the Discrete Choice Analysis model parameters to the future. This is a potential approach to combine the strengths of modeling methods and time series forecasting together to overcome the shortcoming of the currently used new product forecasting methods. As explained in the section on new product forecasting, forecasts for the whole market segment can be obtained through this approach. Hence, time series forecasting methods are also explored to investigate the possibility of formulating a novel dynamic multivariate analysis model, by combining multivariate analysis and time series forecasting algorithms.

2.4 Multivariate Analysis Methods

High-dimensional data with limited number of observations and multicollinearity among product attributes are the typical shortcomings of the design data, as explained in the previous section. Hence, the existing preference/choice modeling methods cannot handle the design data efficiently. Independence of variables is a basic assumption of those modeling techniques, and they require an extremely high ratio between observations and variables to get reliable models.

The most well known multivariate analysis methods are Factor Analysis (FA) and Principle Component Analysis (PCA) (Velicer and Jackson 1990; Chin 1995; Widaman 1993). Generally, PCA is favoured in practical exploration studies, where more weight is given to the prediction abilities (Velicer and Jackson 1990). They have viewed PCA as a more computationally efficient, approximated, factor analysis model. In contrast to this view, in the detailed paper about the history of Factor Analysis and the factor indeterminacy, Steiger and Schonemann (1978) viewed the factor analysis as a computationally intensive, theoretically problematic, approximation of PCA. Especially, they have criticized the Factor Analysis for going beyond the sample space. Therefore, PCA can be viewed as a simple, but efficient method for the multivariate analysis. However, these two methods are only applicable with the analyses involving predictor variables, where the main goal is exploring the relationships among predictor variables. Principal Component Regression (PCR) (Erikssson et al. 2006) is an extension of PCA to handle the response variables.

PLSR and PCR are well known methods to handle multicollinear predictor variables (Yeniay and Goktas 2002). However, PLSR is preferred over PCR due to the unique model structure of PLSR which enables it to overcome the multicollinearity with fewer factors (Yeniay and Goktas 2002). Also, PLSR model parameters are estimated based on the relationship between response variables and predictor variables, in contrast to the predictor variable based estimation process of PCR (Eriksson et al. 2006; Wold et al. 2001). In addition to the effective handling of multicollinearity, PLSR is a well known method to overcome the overfitting. Therefore, PLSR can be used in situations where the number of predictor variables similar or higher than the number of observations; in other words, it can handle the high dimensional data with limited number of observations (Carrascal et al. 2009).

PLSR is one of the most popular multivariate analysis methods in the domain of chemometrics (Wold et al. 2001). In the chemometrics literature, there are many studies depicting its superiority over other multivariate analysis models. Frank and Friedman (1993) presented the statistical views on PLSR, PCR, Ridge Regression and Variable Subset Selection methods with a case study. Frank and Freidman (1993) have recommended PLSR in the cases of high multicollinearity, similar to the result of Yeniay and Goktas (2002).

Thomas and Haaland (1990) presented a comparison of Ordinary Least Squares, Inverse Least Squares, PCR and PLSR. They have recommended the use of PLSR in situations where any prior knowledge about data is not available. Furthermore, there are few more papers published by these two authors comparing popular multivariate analysis methods with PLSR (Haaland and Thomas 1988a; 1988b). According to these previous case studies, the multivariate analysis methods were carefully reviewed to select a method with less data requirements, accurate predictions and model structural properties. Especially, the model structural properties can be used to ensure the structural validity of the projected models.

PLSR and its extension with a layer of LVs, PLSPM, were selected to as the potential modeling methods. PLSPM is analogous to the Structural Equation Modeling based Bayesian hierarchical models (Hoyle et al. 2010) introduced earlier. However, PLSPM is a flexible "soft modeling" method which can effectively handle small sample sizes without any normality assumptions on data (Birkinshaw et al. 1995). Therefore, PLSPM is selected over the Structural Equation Modeling (Kline 2011) for the product value-characteristic modeling. Furthermore, the unique structural properties (Wold et al. 2001) shared by these two modeling methods can be used to check and validate the future models projected by a model parameter forecasting process. The following two subsections provide the background information, structural properties and mathematical formulation of Partial Least Squares techniques.

Partial Least Squares Regression (PLSR)

PLSR is developed by Herman Wold (Eriksson et al. 2006; Wold et al. 2001) to model the complicated data sets, in terms of chains of matrices. NIPALS (Nonlinear Iterative Partial Least Squares) is the algorithm developed to estimate the PLSR parameters. In this algorithm, model parameters are estimated by iterative calculations with respect to the slope of a simple bi-variate or least squares regression.

PLSR has proven its effectiveness in Quantitative Structure Activity Relationship (QSAR) modeling, multivariate calibration and process monitoring optimization (Burns and Ciurczak 2007). The accuracy of the model is increased with the number of relevant predictor variables, **X**. This method can deal with the missing data and relatively small amount of observations successfully. PLSR is used in our method, in view of the fact, the number of observations may be lower and the number of variables to explore in the study can be higher and correlated (Eriksson et al. 2006; Wold et al. 2001).

The unique model structure of PLSR makes it robust to the multicollinearity presence among predictor variables (Eriksson et al. 2006; Wold et al. 2001). PLSR formulates a new axis system inside the predictor variable space via estimated model components. These model components are orthogonal to each other, and they provide the basis for the robust performances of PLSR. In statistical point of view, shrinking the solution coefficient vector away from the directions of low sample variances is the rationale behind the robustness to the multicollinearity (Frank and Friedman 1993). The efficient handling of low sample sizes and multidimensional data can be attributed to the projection of multidimensional data points to the low-dimensional hyper planes spanned by the model components (Wold et al. 2001; Eriksson et al. 2006), as explained in the following paragraphs.

The PLSR model represents the **X** variables by estimated latent variables or their rotations. These new variables are called **X** scores, the orthogonal **t** vectors. The number of estimated score vectors is decided by the number of components used in the PLSR model formulation. **Y** or response variable scores are given by **u** vectors, and **M** and **C** are called **X** and **Y** loadings. In PLSR model formulation, the input variables of **X** are not assumed to be independent of each other. This is realized by an assumption of the existence of latent variables that are related to **t**, and influence **Y** (Wold et al. 2001).

The linear PLSR is graphically illustrated in Figure 2-3. As shown in the figure, a hyper plane is defined by multiple PLSR model components. Each of the model components includes one line and its direction. The direction coefficients of these lines are $\mathbf{P}(k,a)$ values, where The predictor variable is given by k and the model component number is given by a. **X**-scores or $\mathbf{T}(k,a)$ values are obtained by projecting points to the hyper plane, and they are good predictors of **Y**.

NIPALS algorithm (Wold et al. 2001) is given from Equation 2.7-2.17 to depict the mathematical formulation of PLSR parameters. The algorithm starts after pre treating the data (optionally transformed, scaled and centred), which is known as auto-scaling in the PLSR literature.

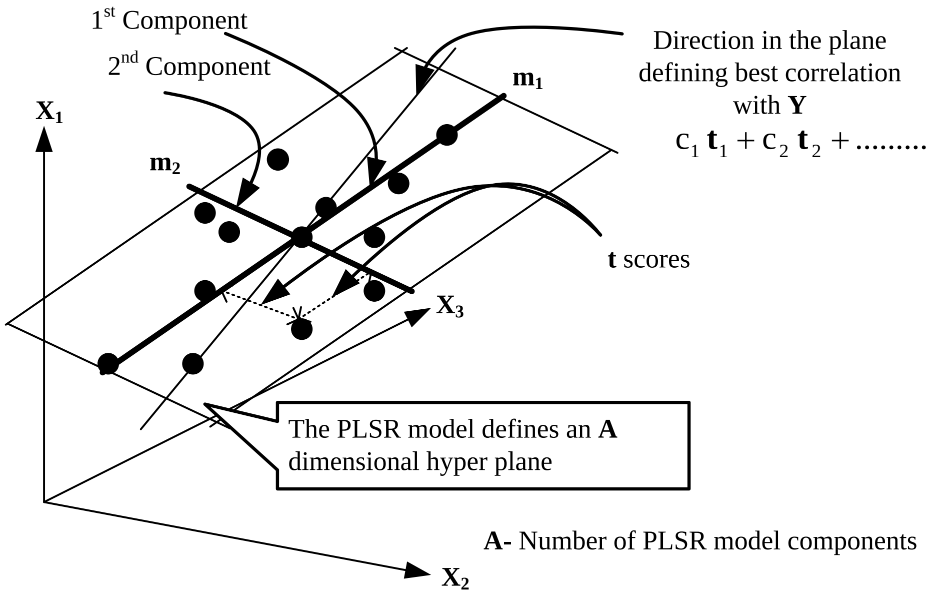

Figure 2-3 Partial Least Square Regression (PLSR) variable space (Wold et al. 2001)

Step 1: Get a starting vector of **u** usually one of the **Y** columns.

$$\mathbf{u} = \mathbf{y} \tag{2.7}$$

Step 2: Calculate the **X** weights **m**, and normalize it.

$$\mathbf{m} = \frac{\mathbf{X'u}}{\mathbf{u'u}} \text{ and normalize } \mathbf{m} \text{ to } ||\mathbf{m}||=1 \tag{2.8}$$

Step 3: Calculate **X**-scores, **t**.

$$\mathbf{t} = \mathbf{Xm} \tag{2.9}$$

Step 4: Calculate the **Y**-weights, **c**.

$$\mathbf{c} = \frac{\mathbf{Y't}}{\mathbf{t't}} \tag{2.10}$$

Step 5: Update the **Y** score, **u.**

$$\mathbf{u} = \frac{\mathbf{Yc}}{\mathbf{c'c}} \tag{2.11}$$

Step 6: Check convergence of **t**.

$$\| \mathbf{t}_{new} - \mathbf{t}_{new} \| / \| \mathbf{t}_{new} \| < \varepsilon \text{, where } \varepsilon \text{ is the tolerance (e.g., } 10^{-6}) \qquad 2.12$$

If the convergence has not been reached, then return to the Step 2, else continue to the next step.

Step 7: Deflate present components from **X** and **Y,** and use the deflated matrices as new **X** and **Y** in the next component calculations. Deflation of **Y** is optional.

$$\mathbf{p} = \frac{\mathbf{X't}}{\mathbf{t't}} \qquad 2.13$$

$$\mathbf{X} = \mathbf{X} - \mathbf{tp'} \qquad 2.14$$

$$\mathbf{Y} = \mathbf{Y} - \mathbf{tc'} \qquad 2.15$$

Step 8: Continue with the next component starting from Step 1 to Step 7, until cross validation (see below) indicates no more significant information in **X** about **Y** (Wold et al. 2001).

The score matrices **T**, **U** and the loading matrices **M**, **P** are formed by **t**, **u**, **m** and **p** columns obtained in the above algorithm runs. After *f* times iterations, the obtained model holds the relations in Equations 2.16 and 2.17.

$$\mathbf{X} = \mathbf{TP}' + \mathbf{X}_{\mathbf{f+1}} \qquad 2.16$$

$$\mathbf{Y} = \mathbf{UC}' + \mathbf{Y}_{\mathbf{f+1}} \qquad 2.17$$

The terms $\mathbf{X_{f+1}}$ and $\mathbf{Y_{f+1}}$ are the residuals of the model. The number of runs, A must be carefully chosen in order to ensure that no correlation is found between residuals. The goodness of fit and the goodness of prediction (cross validation) are used to choose the maximum number of model components or runs A. The goodness of fit is denoted by R^2 and Q^2 notation is used for the goodness of prediction. The residual and data sum of squares are used to calculate the goodness of fit.

$$R^2 = 1 - [SS_{residual} / SS_{data}] \tag{2.18}$$

Q^2 or goodness of prediction is calculated using cross validation. Observations are divided into sub groups. Without one of the sub groups, a model is obtained to calculate the residuals. This process is carried out for all sub groups. Then, Q^2 is obtained similarly to the R^2 calculation.

$$Q^2 = 1 - [SS_{predict.residual} / SS_{data}] \tag{2.19}$$

R^2 increases as the number of components does. Q^2 increases as R^2 does at the beginning, but at some point it begins to decrease due to the over fitting of the model to the calibration set. Hence, the number of components should be obtained to optimize the goodness of prediction (Eriksson et al. 2006; Wold et al. 2001).

The **M**, **P** and **C** matrices obtained in the model estimation process stated above are used to predict new observation. Predictions of new observations, $\mathbf{X_0}$, are calculated using Equation 2.20.

$$\mathbf{Y}_0 = \mathbf{X}_0\mathbf{M}(\mathbf{P'W})^{-1}\mathbf{C'} \tag{2.20}$$

The matrix obtained by the linear algebraic operation, $\mathbf{M(P'W)^{-1}C'}$, is called regression coefficient matrix and it is denoted by **B**.

$$\mathbf{B} = \mathbf{M}(\mathbf{P'W})^{-1}\mathbf{C'} \tag{2.21}$$

The important information of the relationship between **X** and **Y** (i.e., contribution of **X** towards **Y**) is provided by the regression coefficient matrix, **B**. This coefficient vector represents the value-attribute relationship in the market segment, when used for a market analysis. Anyway, in this research study, more attention is paid to the model parameters, due to their attractive structural properties. These properties can be used to check and control the model parameter forecasting process.

Partial Least Squares Path Modeling (PLSPM)

PLSPM is a "soft-modeling" technique invented to use in the social sciences, where the requirements of methods such as structural equation modeling, are difficult to fulfil (Dijkstra 2010). The main objective behind the introduction of PLSPM was the effective handling of multidimensional data in low structural environments (Vinzi et al. 2010a; Vinzi et al. 2010b).

PLSPM model structure is depicted in Figure 2-4. Inner and outer models are the two integral parts of a PLSPM. The inner or the structural model consists of relationships in between latent variables (LVs, given by **L),** which are not directly measurable. The outer model consists of manifest variables (MVs, given by **Z**), or indicators used to measure or form a LV (Vinzi et al. 2010b). The outer model can be divided into two parts according to types of indicators used for the model formulation. The two types are the formative model, which contains LVs generated by MVs, and the reflective model, which contains the LVs reflected by MVs.

PLSPMs are estimated using the fixed point estimation algorithm (Vinzi et al. 2010b). The inputs to the algorithm are the Q blocks of centred MVs, $\mathbf{Z}=[\mathbf{Z}_1,....,\mathbf{Z}_q,.....,\mathbf{Z}_Q]$, where Q is the number of LVs. The fixed point estimation is given below.

Step 1: Initialize $\mathbf{w}_q$

Step 2: New $\mathbf{L}_q$ estimate

$$\mathbf{L}_q = \pm \mathbf{X}_q\mathbf{w}_q \quad \text{Outer estimation} \tag{2.22}$$

Step 3: Estimate $\mathbf{e}_{qq}$

$$\mathbf{e}_{qq'} = \text{sign}[\text{cor}(\mathbf{L}_q,\mathbf{L}_{q'})] \text{ LVs q and q' are connected} \tag{2.23}$$

Step 4: Update $\mathbf{L}_q$

$$\boldsymbol{L}_q = \pm \mathbf{e}_{qq}\mathbf{L}_{q'} \quad \text{Inner estimation} \tag{2.24}$$

Step 5: Use PLSR to update $\mathbf{w}_q$

Check for convergence of $\mathbf{w_q}$

If {max(w_q current iteration – w_q previous iteration)< Δ} **Break** Else Go to **Step 2**

Upon convergence of $\mathbf{w_q}$

$\boldsymbol{l}_q = \pm \mathbf{X}_q\mathbf{w}_q$, Compute standardize LV scores 2.25

$\boldsymbol{\beta}_j = (\Xi'\Xi)^{-1}\Xi'\ \Xi\ \boldsymbol{l}_q$, Where Ξ includes the LVs that explain the j^{th} LV 2.26

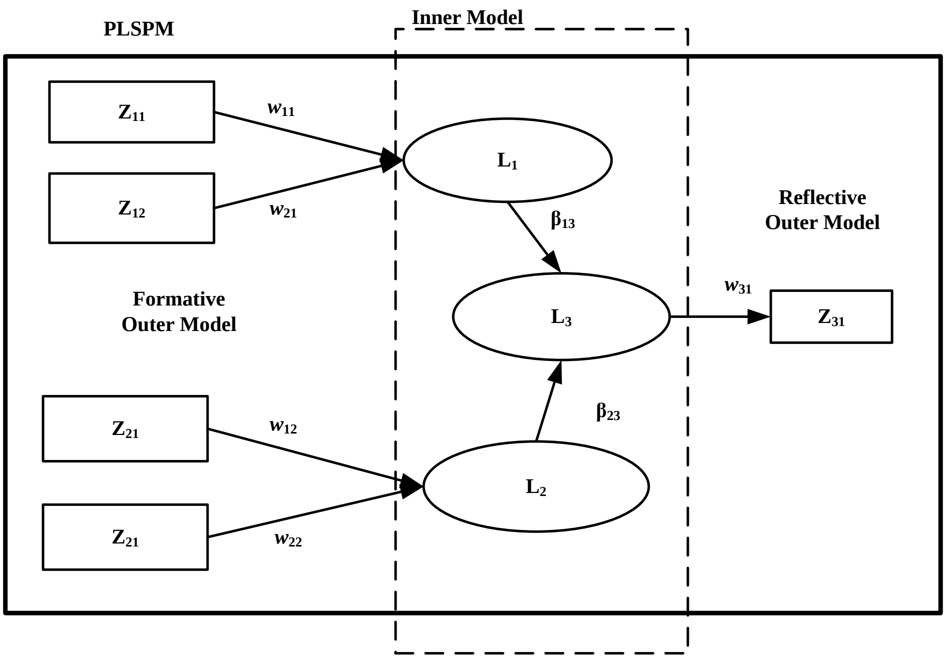

Figure 2-4 Partial Least Square Path Modeling (PLSPM) Model Structure

Many layers of PLSR models can be observed inside a PLSPM, since PLSR is used as the parameter estimation method. These three layers are called as the formative model, the inner model, and the reflective model, which are the integral parts of a PLSPM. All the indicator values are fed to the PLSPM estimation algorithm to estimate inner path coefficients (**β**) and outer weights (**w**) (see Figure 2-4). The iterative estimation process stops when the outer loadings are converged, and a more generic algorithm is given (Vinzi et al. 2010b).

Goodness of fit (GoF) is the main quality index used in PLSPM (Vinzi et al. 2010b; Chin 2010a; Chin 2010b). GoF calculations involve two other indices: the communality index and the R^2 value of the structural model. Average communality ($\overline{Com}$ in Equation 2.27) measures the strength of the relationship between MVs and LVs using the squared correlation (cor^2) between them.

$$\overline{Com} = \frac{1}{\sum_{q:P_q>1} P_q} \sum_{q:P_q>1} \sum_{p=1}^{P_q} cor^2(x_{pq}, \hat{L}_q) \quad 2.27$$

The average R^2 measures the strength of the structural model, or the inner model. The number of endogenous LVs in the model is given by J.

$$\overline{R^2} = \frac{1}{J} R^2(\hat{L}_q, \hat{L}_{q:L_q:\rightarrow L_j}) \quad 2.28$$

Eventually, GoF can be calculated using the average communality and the average R^2 as given in Equation 2.29.

$$GoF = \sqrt{\overline{Com} \times \overline{R^2}} \quad 2.29$$

Structural equation modeling, the counterpart of PLSPM in "hard" statistical modeling, is ineffective without 200 or more observations, which are used to formulate a decent model with few variables (Kline 2011). In contrast, PLSPM works with smaller data sets without any assumptions regarding distributions, and is not computationally intensive. This makes PLSPM an attractive choice for modeling the customer satisfaction-product attribute relationship; especially, in the RP type of analyses.

2.5 Statistical Time Series Forecasting

Time series forecasting techniques are mainly used for the industrial demand forecasting applications. They are used to model the systematic components of a time series, which can be captured by statistical methods. Levels, trends, and seasonality are the systematic components, and the most prominent components can be captured using a suitable forecasting technique. However, it is impossible to find a perfect forecasting technique or to get perfect forecasts, due to the random components presents in time series (Chopra and Meindl 2001; De Gooijer and Hyndman 2006; Kahn 2002).

In the 19th century time series were considered as deterministic entities, without any random components. Yule (1927) changed that school of thought with his major contribution, which introduced the notion of stochasticity, or the random components of a time series. This led to the currently used postulate; a time series is a realization of a stochastic process. Many new forecasting methods were initiated by his new vision.

Currently, Moving Average (MA) and exponential smoothing are the most popular methods used to handle small historical observation sets. Anyway, out of the vast array of univariate forecasting methods, exponential smoothing methods can be considered as one of the most powerful method, in addition to their low historical data and computational requirements (Gooijer and Hyndman 2006).

Initially, exponential smoothing methods were considered as ad-hoc methods, though they are well accepted, widely used methods nowadays. They were not treated well within academic circles, due to the absence of a sound statistical foundation. Although, Brown (1959), and Holt and Winters (Holt 1957; Winters 1960) contributed with their versions of exponential smoothing methods, they had to wait for the statistical foundation for Single Exponential Smoothing (SES) provided by Muth (1960) to get the recognition for their contributions.

Exponential smoothing was enhanced by Gardner (1985) and Snyder (1985) articles, which provided the initial thrust for much more subsequent works. Also, they established a link between exponential smoothing and state space models. Now, exponential smoothing is a highly recognized forecasting techniques family, which has got many branches. There are methods which can be used to estimate from the basic levels to more advanced seasonal impacts.

The advanced forecasting methods, such as Autoregressive (AR) and Autoregressive Integrated Moving Average (ARIMA) (Newbold 1983), can be used with the availability of more historical observations. Autoregressive (AR) models were conceptualized by Slutsky, Walker, Yaglom, and Yule (De Gooijer and Hyndman 2006), based on Yule's new approach (1927). A completely new discipline in the area of time series was created, after solving the linear forecasting problem of Kolmogorow (1941), using Wold's decomposition theorem. A considerable amount of literature appeared, inspired by the above solution, dealing with the parameter estimation, identification, model checking, and forecasting (Newbold 1983). Finally, Box and Jenkings (1970) provided a much needed frame work for the Auto Regressive Moving Average (ARMA) based forecasting, in their highly valued book.

The Vector ARIMA (VARIMA) and Vector ARMA (VARMA) models are multivariate generalizations of the univariate ARIMA and ARMA models. The population characteristics of VARMA appear to have been first derived by Quenouille (1957), although software to implement them only became available in the 1980s and 1990s. Other than these two methods there are many non linear and linear methods used for the multivariate forecasting such as ANN (artificial neural networks) and functional coefficient models (De Gooijer and Hyndman 2006).

In this research study more attention is paid to simple, theoretically sound techniques with minimum observational requirements. The case studies conducted in the thesis are limited to smoothing methods, due to limitations in availability of historical data. ARIMA and most of the advanced forecasting techniques require more than 40 historical data points to get accurate results (Bisgaard and Kulahci 2011). Practically, it is difficult to fulfill the higher data requirements of the advanced forecasting techniques, in most of the times.

Multivariate analysis methods can be used to capture the relationships between the predictor and response variables, and these relationships are reflected by the model parameters. On the other hand, time series forecasting techniques can be used to capture the systematic variations of any time series. Hence, multivariate analysis methods can be integrated with time series forecasting techniques to project the model parameters to the future. This is recognized as the potential approach to formulate dynamic preference models for the technological market segments. Most importantly, the model structural properties can be used to get a valid future model by controlling the forecasting process.

The dynamic preference model is proposed to use as the decision support tool of the Strategic Decision Support Framework for the front-end product concept screening process. Furthermore, the thesis contributions are targeted at the research gaps in the current design practices. Hence, a well accepted design theory and method validation strategy in the PDD research community, validation square, is recognized as the best available approach to validate the contributions of the thesis. An introduction of the validation square validation approach, and the key validation steps are given in the following section.

2.6 Validation Square approach in Design Method and Research Validation

Validation of the newly formulated design methodology is the ultimate task of this research study. Validation Square (Pedersen et al. 2000) is the approach that will be used in the task of validation.

Validation square enfolds six steps critical in validating a design methodology (see Figure 2-5). These six steps ensure rigorous testing of structural validity and performance validity of the design method. First three steps check qualitative aspects or effectiveness of the method. Next three steps check the efficiency of the method and evaluate its quantitative aspects.

The six step validation process is given below.

Step 1: Accepting the individual constructs constituting the method

Step 2: Accepting the internal consistency of the way the constructs are put together in the method

Step 3: Accepting the appropriateness of the example problems that will be used to verify the performance of the method.

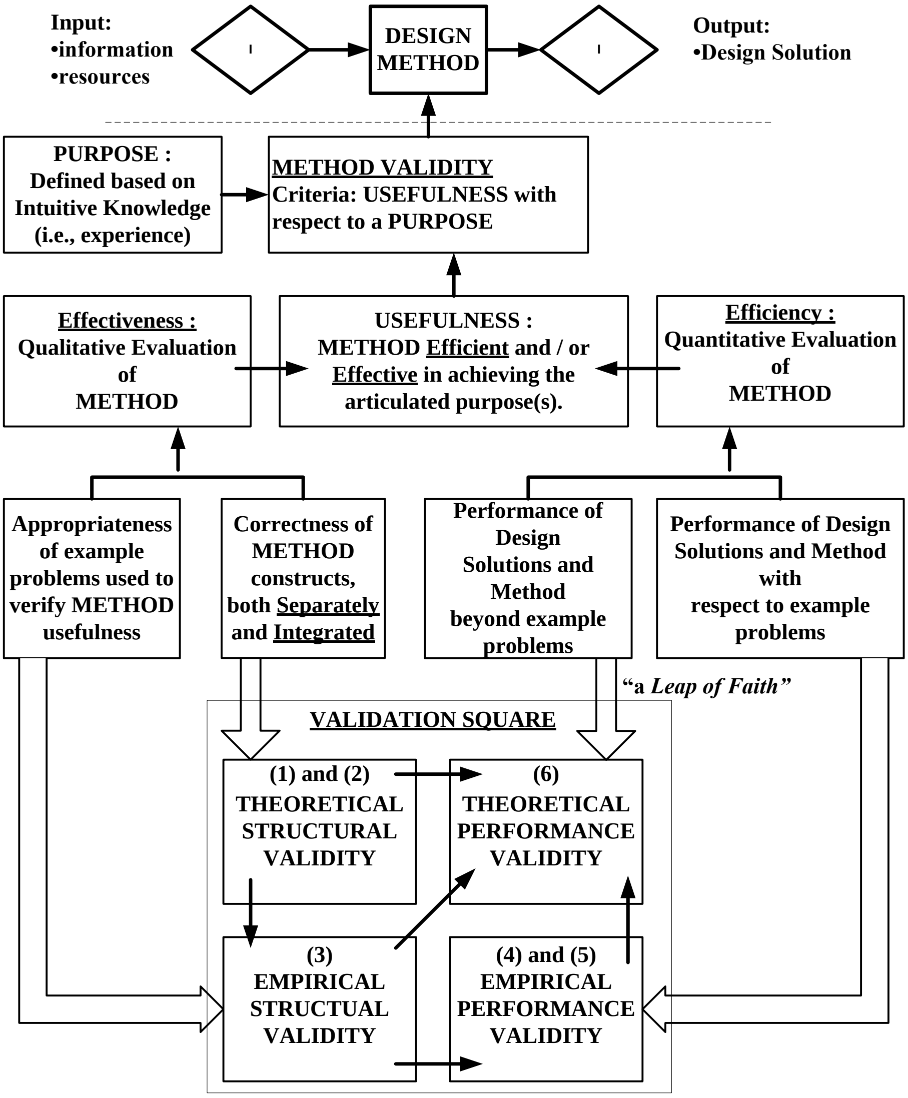

Figure 2-5 Validation square and validation process (Pedersen et al. 2000)

Step 4: Accepting that the outcome of the method is useful with respect to the initial purpose for some chosen example problem(s);

Step 5: Accepting that the achieved usefulness is linked to applying the method; and

Step 6: Accepting that the usefulness of the method is beyond the case studies.

Theoretical structural validity testing is done in the literature review and introductions of each component used to formulated the proposed framework. The next two steps, empirical structural and performance validity are mainly consists of case study verification and results validation activities. Finally, the whole framework can be accepted after completing first three steps. Usually further generalization is done by using case studies from other areas. Also, the usefulness of the method can be recognized and further case studies can be suggested as future works in the conclusions.

The system level overview of the proposed framework, the potential components and the validation process are covered up to this section. The next section clearly defines the research gaps and further narrows down the scope of the research study. This is an essential step before formulating the research questions.

2.7 Research Gaps

The literature review, containing the background and the potential components of the proposed framework, is used to identify the research gaps in current design methodologies. Thus, Product value is identified as a widely used metric of customer satisfaction in marketing analyses.

The standard industrial practice is to use a Stated or Revealed Preference analyses method to estimate the product value and the value-attribute relationship at once. The important observations from the current Stated and Revealed Preference modeling methods are given in Table 2-2. The Revealed Preference type data, reputed to be more reliable by nature, is not used efficiently in the current PDD activities. It is only used for short term product development tasks. Also, currently used modelling methods are not equipped to handle the multicollinearity, endogeneity and heteroscedastic errors effectively, as mentioned earlier.

The product value-attribute relationship provides information about how product attribute levels influence the overall product value. In addition, there are extended analyses including LVs or higher level product characteristics (system level product attributes) (Hoyle et al. 2010). The LV model structure or the relationship between LVs, and how they influence each other provides more information and insights about the market segments. Currently, the LV modeling approach is relied on Maximum Likelihood Estimations (MLE) for the model parameter estimation (Kline 2011). It has higher data observation requirements, in addition to the high sensitivity to above mentioned errors. Also, Revealed Preference type LV models, based on value driven design approach, are not available in the literature.

Table 2-2 Summary of literature review and their significance to the research study

Topic	Important points	Significance to the research study
Stated and Revealed Preference Methods	Revealed Preference methods are only used to evaluate existing alternatives (Louviere et al. 2000)	Projecting of Revealed Preference functions to future will provide a new way to asses new introductions
	Independence of variables is a basic assumption of most of the statistical methods use in this area (Wassenar et al. 2005)	A new statistical method is needed to avoid the violation of assumptions

A novel method is needed to project the Revealed Preferences beyond the current technological boundaries, and use them for the conceptual design evaluation. A dynamic model, which can be used to forecast the customer satisfaction generated by conceptual products, is a potential approach to overcome this problem (Kim et al. 2005).

Kim et al. (2005) proposed a two pronged approach for dynamic modeling. Firstly, they formulated a static Discrete Choice Analysis model series, and arranged the model parameters into a time series. Secondly, they used time series forecasting techniques to generate model parameter forecasts, considering the model parameters are time series observations. Hence, obtaining a static model series, robust to the errors and shortcomings in design data, is the foremost important task. In addition, an advanced dynamic modeling method is needed to extend the dynamic value-attribute relationship to include LVs to represent the higher level product characteristics. Mainly, three research gaps can be identified in the currently available literature.

1. ***Absence of a robust product value-attribute modeling method:*** A robust product value-attribute model is needed to handle the multicollinearity presence in the design data. Also, it should be able to provide valid models with high dimensional data and low numbers of observations. The modeling errors common to preference models, endogeneity and heteroscedastic errors should be minimized in this modeling method.

2. ***Absence of a structurally sound dynamic product value-attribute modeling method:*** A structurally sound dynamic product value-attribute model is not available in the current literature. A novel dynamic modeling method is needed to represent the market dynamics in the front-end product concept screening process.

3. ***Absence of a dynamic LV value modeling method:*** The LV models with higher product characteristics are important to understand the market segments, as explained earlier. Revealed type LV models, based on value driven design, are not available in the PDD domain. In addition, a dynamic LV modeling method will be a completely new contribution.

The importance of the above mentioned research gaps can be highlighted using the definitions of uncertainties in system modeling. Mainly, there are three types of uncertainties in system modeling: natural uncertainty, data uncertainty, and model uncertainty (Iskukapalli et al. 1998; Choi and Allen 2009; Choi et al. 2005). Natural uncertainty is caused by the inherent randomness of the system, and data uncertainty is caused by inaccuracies in data. Model uncertainties are caused by simplifications and approximations of real systems in models formulated to represent them.

The popular revealed and Stated Preference analyses are based on the assumptions of time-invariant preferences: in other words, the oversimplification of dynamic preferences as expressed through a static model. In addition to the simplified preferences, model uncertainties are caused by the violation of assumptions in current preference modeling methods. The shortcomings of the technological product attribute data can affect the current modeling methods. Thus, the current modeling approaches are prone to the endogeneity and heteroscedastic errors.

The research questions are formulated in Chapter 3 to find solutions to these important research gaps. The main contributions of the thesis are presented from Chapter 4, depicting the formulation process and applications of the proposed Strategic Decision Support Framework.

3 Value Driven Design Decision Making

3.1 Strategic Decision Support Framework

In this section the concept of Strategic Decision Support Framework is described with the aim of research question formulation. An overview of the proposed Strategic Decision Support Framework is depicted in Figure 3-1 to clearly define the proposed framework and related PDD activities.

Strategic Decision Support Framework projects a future customer requirement function, in contrast to the current practice of product concept screening based on an initial customer requirement analysis. In the proposed framework, the attribute levels (**X**) of product concepts are used as the inputs to get the future product value (**Y**) outputs, considering the effect of the concept-to-customer lead time on customer preferences. According to the proposed framework, the best product concepts are selected based on the future product value estimations. Hence, Strategic Decision Support Framework can be used to incorporate the dynamic nature of the customer preferences into the front-end product concept screening process.

The research questions are formulated to address the research gaps identified in the previous chapter. The proposed approaches to address the research gaps are given immediately following the research questions.

Research Question (RQ 1)
RQ1. How to obtain a robust value-attribute model?

A multivariate analysis method, PLSR, is proposed as the modeling technique to address this research question. The main strengths of PLSR, the robustness to the multicollinearity presence among variables and its ability to handle high-dimensional data with a low number of observations, can be used effectively to overcome the challenges identified earlier.

Modeling the pure characteristic value of a product is proposed as an approach to overcome the price endogeneity. The price-attribute trade-off is excluded from the model to get pure characteristic representation. Also, ability to handle multicollinearity will minimize the number of important variables screened out during the model formulation process. As a result, endogeneity will be minimized with the use of PLSR.

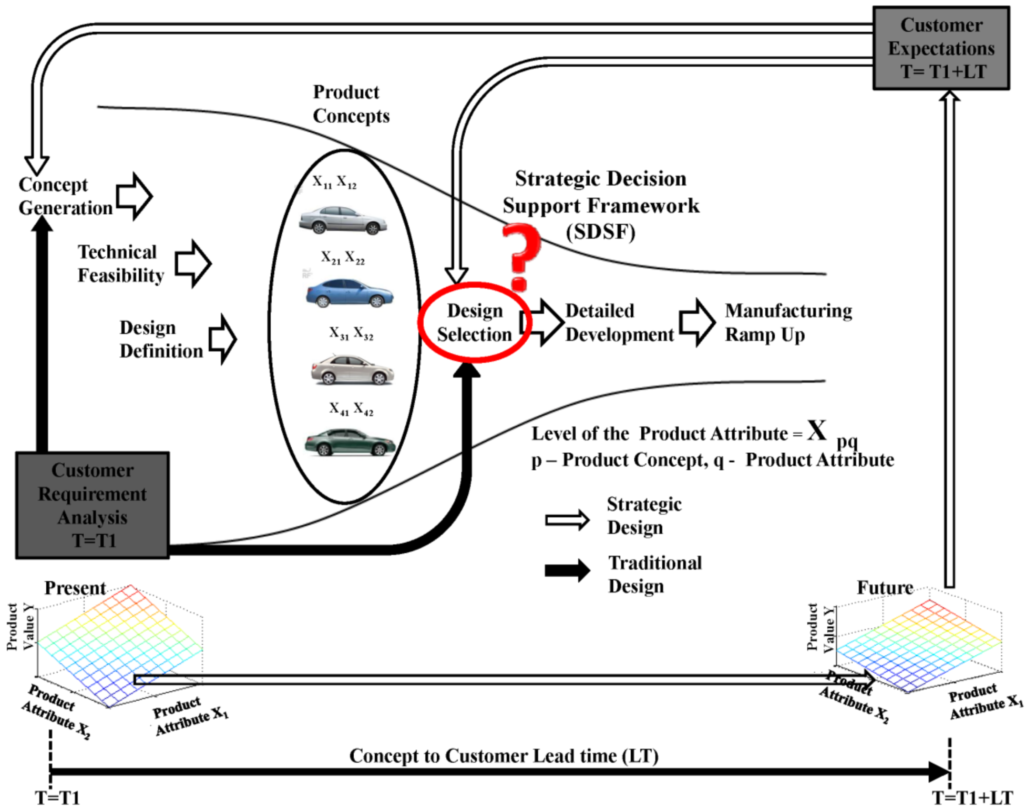

Figure 3-1 Strategic Decision Support Framework (Withanage et al. 2010b)

CRV, the value metric of the Value Driven Design, is proposed as the approach to estimate the pure characteristic value of products. It provides the perceived values of products, which can be estimated with a less effort. However, the product market segment should be correctly identified to get accurate CRV estimations. Especially, identifying the competing products from the product market segment is the first and the foremost important task of the CRV estimation process (Donndelinger and Cook 1997). A set of products with comparable product attribute levels, catering a sub-set of customers with common requirements, can be identified as a product market segment (Simpson 1998). CRV is estimated using a straight forward demand-price analysis (Donndelinger and Cook 1997), which can be conducted with the product market segment demands, prices and price elasticity. Therefore, use of CRV as the customer satisfaction metric can save the resources needed by the Stated Preference methods to elicit the product values.

The variance function estimation approach is proposed as the solution to minimize the heteroscedastic errors. A new algorithm is proposed to formulate this robust PLSR, following the weighted least squares approach.

Research Question (RQ2)

RQ2. How to obtain a dynamic product value-attribute relationship?

A dynamic PLSR modeling method was proposed as the solution to the second research question. The dynamic modeling method is proposed to minimize the model uncertainty, due to the market dynamics, found in current static preference modeling methods. A combination of the PLSR algorithm and the time series forecasting algorithms is proposed as the approach to formulate the dynamic model. Furthermore, the structural properties of PLSR models can be used to control the parameter forecasting process and preserve the structural soundness of the projected future models.

Research Question (RQ3)

RQ3. How to obtain a dynamic Latent Variable (LV) value model?

A dynamic PLSPM method is proposed as the solution, extending the dynamic value-attribute relationship, by including higher level product characteristics. The higher level product characteristics are represented by LV scores (**L**) in the dynamic PLSPM method. The proposed dynamic PLSR method can be used as the basic building block to formulate this extended LV value model.

3.2 The Organization of the Thesis

The logical flow of the thesis and the main contributions are given in Figure 3-2 to present the connection between the chapters, research questions, hypotheses, and to give an idea about the overall validation process.

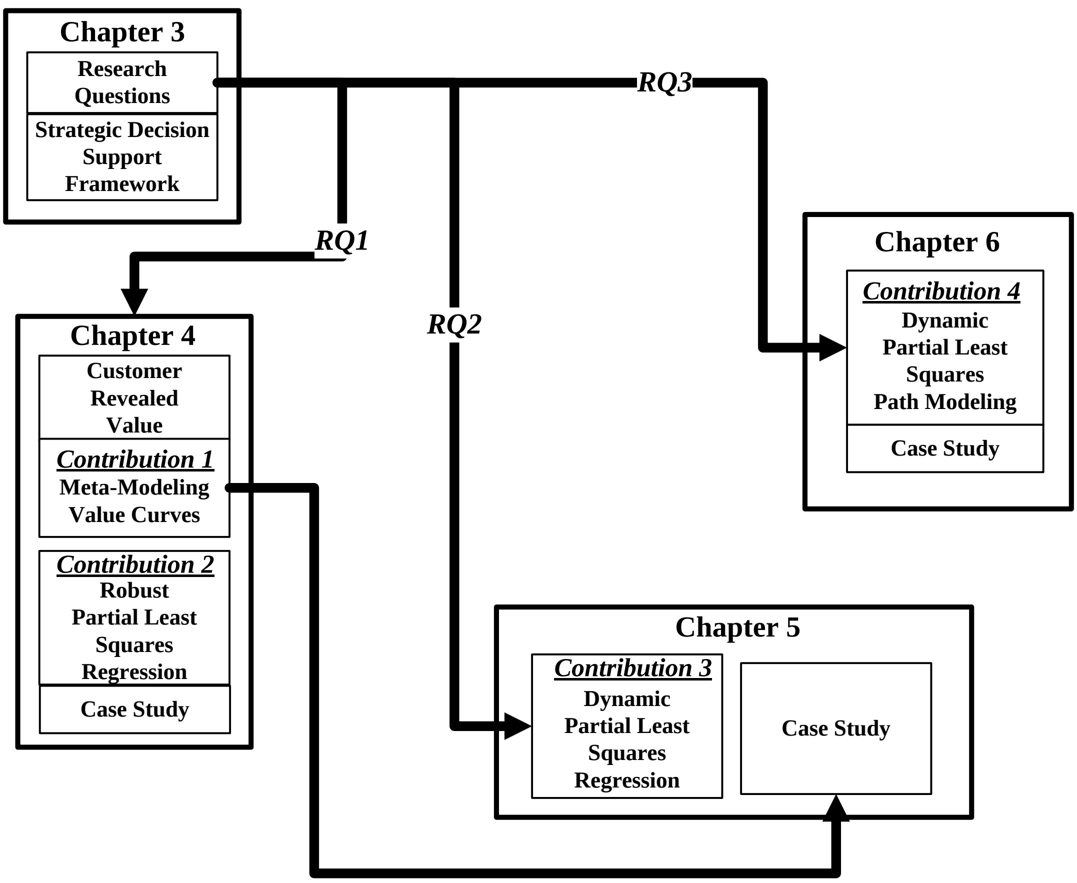

Figure 3-2 Organization of the thesis

Chapter 4, Chapter 5 and Chapter 6 contain the main contributions of the research study towards formulating the novel Strategic Decision Support Framework (see Figure 3-2). The static product value-attribute modeling is introduced in the Chapter 4, as a solution for the first research question. The main contributions of this chapter are the product value-attribute meta-model and the robust PLSR modeling. A robust modeling method, introduce in this chapter, extends PLSR to effectively handle the heteroscedasticity.

The Chapter 5 contains Dynamic PLSR modeling method, and the Chatper 6 presents Dynamic PLSPM. The path modeling is an extended version of the regression modeling approach, with LVs or higher level product characteristics, as explained earlier. These dynamic models are novel modeling methods formulated to address the specific need of reducing model uncertainty.

Many constructs are used from various domains in formulating the proposed framework. Only the well established constructs are carefully chosen to avoid any additional errors. Hence, the theoretical structural validation is limited to a presentation of the underlying theories and supporting research studies. However, the structure of the framework is rigorously checked to ensure the consistency of the constructs combined together to make the proposed Strategic Decision Support Framework.

The case studies are used in order to empirically validate each and every component of the framework. A special attention was given to construct the case studies to mimic typical decision making tasks in PDD. US Sedan car market segment (see Appendix A) is selected as the market segment for the empirical testing ground. Sedan cars are a well established technological product market segment with many competing brands and car model series, which represent the highest fraction of sales in the overall US automobile market. The selected product platform is nearly half a century old, and the saturated technologies combined with high competition make customer driven design an ideal solution.

The presented case studies were narrowed down to the family Sedan market segment, using a three step screening process. Firstly, 4 door Sedan car models, from the US light passenger vehicle market segment, were screened out to get the set of total product market segment observations. Secondly, the mid and compact size cars, out of the selected 4 door Sedan car models, were selected to represent the family Sedan market segment. Finally, the most popular mid range Sedan car models were selected by chopping off the lower tail of the demand distribution and upper tail of the price distribution to exclude the high-end luxury cars. In this process, the final selected set of yearly observations was maintained to represent more than 75% of the total yearly Sedan car market segment sales, in order to get an accurate product market segment representation.

Demands, prices and main specification data sets of the product market segment were obtained from Ward's Automobile Group, a well known market analysis provider. Some specification data was manually collected from the popular reliable websites, such as Consumer Reports, Kelly's Blue Book, Edmunds.com, J.D Power and Associates and Yahoo Auto. The results of the conducted case studies were used for the empirical performance validation. The main contributions of the research study are presented in the following chapters. Finally, the conclusions are provided to identify the main practical and theoretical contributions, limitations and the potential future works.

4 STATIC VALUE-ATTRIBUTE MODELING

4.1 Meta-Modeling of Value Curves

A decision support variable is an essential component of any Decision Support Framework. CRV (introduced in Section 2.2), a value metric from Value Driven Design (Cook and Kolli 1994) framework, is used as the decision variable in the case studies presented in this thesis. This section provides the theoretical background of CRV and the derivation of the value-attribute meta-model for the market segment preference representation.

The product value-attribute meta-model is used to estimate the CRVs of conceptual products, providing a solution for the first research question. In this meta-model, CRV is used as the response variable and product attributes are used as the predictor variables. Thus, attribute levels of product concepts are the inputs to the meta-model and it provides the CRV predictions. This meta-model is the main decision support tool used in the proposed Strategic Decision Support Framework (Withanage et al. 2010b). In the proposed framework, the future CRV predictions of the product concepts are used for the front-end product concept screening process, considering the effect of the concept-to-customer lead time. However, the model formulation and the case study are presented in Chapter 5, because this is the initial step of the Dynamic PLSR modeling approach. The derivation of the meta-model from the value curve relationship, the first contribution of the thesis, is given in the following paragraphs.

Theoretical formulations of CRV and value curves are given in Section 2.2 under the topic Value Driven Design. In order to formulate the meta-model, it is convenient to express the overall product value, given in Equation 2-6, in a polynomial form. Also, optional features are assumed to be negligible, and all attributes are assumed to be well defined. The formulation steps are as follows.

Taking logarithms on both sides of Equation 2-6,

$$\log(V) = \log(V_0) + \sum_{i=1}^{k} \log\{v(g_i)\}. \quad 4.1$$

Given Equation 2-4, the logarithmic value of each attribute *i* is

$$\log\{v(g_i)\} = \gamma \log\left\{1 - \left(\frac{g_i - g_I}{g_c - g_I}\right)^2\right\} - 2\gamma \log[g_c - g_I] - \gamma \log\left\{[g_c - g_I]^2 - [g_o - g_I]^2\right\}. \quad 4.2$$

The last two terms inside the logarithm term on the right hand side of Equation 4-2 are constants. The first term is always differentiable since $0 < \{[g_c - g_I]/[g_o - g_I]\}^2 < 1$. Therefore, Equation 4.2 can be converted into a quadratic expression, in terms of g_i, using Taylor Series expansion. Equation 4-2 becomes

$$\log\{v(g_i)\} = c_i - \gamma_i \sum_{n=1}^{\infty} \frac{z_i^n}{n}, \quad 4.3$$

where z_i and c_i given by the following equations.

$$z_i = z(g_i) = \left(\frac{g_i - g_I}{g_c - g_I}\right)^2 \quad 4.4$$

$$c_i = -2\gamma \log[g_c - g_I] - \gamma \log\left\{[g_c - g_I]^2 - [g_o - g_I]^2\right\} \quad 4.5$$

Substituting Equation 4-3 to 4-1, the logarithmic overall product value is

$$\log(V) = \beta_0 + \gamma_i \sum_{i=1}^{k} \sum_{n=1}^{\infty} \frac{z_i^n}{n}. \quad 4.6$$

The constant term is given by $\beta_0 = \log(V_0) + \gamma_i \sum_{i=1}^{k} c_i$. Taking the first term of the Taylor series expansion and ignoring the higher order terms,

$$\log(V) = \beta_0 + \gamma_i \sum_{i=1}^{k} z_i . \quad 4.7$$

The g_C and g_I in z_i are constants (see Figure 2-3). Expanding $[g_i\text{-}g_I]^2$ term and adding all the constant terms, we can express the logarithmic overall product value as

$$\log(V) = \beta_0 + \sum_{i=1}^{k} \left\{ \beta_{i,1} gi + \beta_{i,2} g_i^2 \right\}. \quad 4.8$$

Ultimately, the logarithmic overall product value can be approximated as a second order polynomial form, a simplified meta-model, of product attributes without interaction terms. This relationship is used to formulate the Dynamic PLSR (Withanage et al. 2010b) model given in Chapter 5. The relationship between multidimensional product attribute space the value metric CRV is formulated by PLSR models to obtain reliable prediction models (Wold et al. 2001). Empirical performance testing of this meta-model, the initial step of the Dynamic PLSR modeling, is embedded in the case study presented in Chapter 5.

4.2 Robust Partial Least Squares Regression (PLSR)

The Robust PLSR algorithm is formulated to minimize the effects of heteroscedasticity presence in the training data sets. The proposed method is based on variance function estimation method (Davidian and Carroll 1987), and inspired by the iterative weighted least squares algorithm used in Isukapalli et al. (1998) to address the heteroscedastic error variances of repeated measurements.

Especially, the proposed robust modeling method is useful in situations, where aggregation of data panels (yearly, montly, etc. sets of observations) is needed to get sufficient observations. This is a usual practice in revealed preference studies (Downen et al. 2005), and observation aggregation in this case is analogues to the multiple responses found in the experimental studies with repeated measurements (Isukapalli et al. 1998; Choi and Allen 2009). In the data aggregation approach, the product models or observations are combined from different time frames or data panels. CRVs are changing with the product sales and price changes in different data panels. Therefore, even the product models with exactly matching product attribute levels can have two CRV values in two data panels. These multiple responses for a set of predictor variable values increase the chances of having a heteroscedastic error variance similar to the repeated measurements (Isukapalli et al. 1998; Choi and Allen 2009), and getting erroneous CRV predictions. Ultimately, the front-end concept screening process can be affected by the erroneous CRV predictions of the conceptual products.

Although, PLSR is a soft modeling method, its roots are going back to the commonly used ordinary least squares estimation method. Inside the NIPALS algorithm, a close inspection will reveal few ordinary least squares estimations used for PLSR parameter estimations. Hence, PLSR is also based on the basic assumption of uniform error variance throughout the sample space. Validity of the PLSR models and accuracy of their predictions can be deteriorated, when the training data sets are polluted with heteroscedastic noises (Woodward et al. 1998; Eriksson et al. 2006).

Davidian and Carroll (1987) proposed a conditional variance modeling method to estimate the variances, regarding to the position of the predictor space. Choi and Allen (2009) used a pseudolikelihood function to estimate the variance parameters to come up with a new robust response surface model. The weighted PLSR algorithm is a multivariate extension of weighted least squares modeling method (Choi and Allen 2009; Isukapalli et al. 1998; Neter et al. 1996) to get a more generalize robust PLSR modeling algorithm.

4.3 Robust Product Value-Attribute Model Formulation

The overall procedure of the Robust PLSR model formulation is depicted in Figure 4-1. Especially, the changes happening inside the variable space are included to visualize the procedure. This algorithm starts with the auto-scaling as any other PLSR. After auto-scaling, a

PLSR model is formulated as the initial model. Using the initial model, residuals are calculated for the variance function estimation process.

The variance parameters are estimated according to the variance model suggested by Box and Meyer (1986). It is a widely used variance model in industrial practices. According to the Box and Meyer, heteroscedastic error variances can be modelled by Equation 4.9.

$$\sigma_i^2 = \exp(\boldsymbol{\theta}.\mathbf{x}_\mathbf{i}^{'}) \tag{4.9}$$

Where, i=1,……., N (number of observations),and $\boldsymbol{\theta}$ is a vector of variance parameters. The residuals are calculated using the initial PLSR coefficient vector $\widehat{\boldsymbol{\beta}}$. The vector of variance factors assumed to be $\mathbf{x}_\mathbf{i}^{'}$**,** the predictor variables in this case. The initial $\boldsymbol{\theta}$ is set to a vector of ones.

Residual sum of squares, pseudolikelihood and logarithm functions can be used for the variance parameter estimation process (Davidian and Carroll 1987; Choi and Allen 2009). However, the logarithm least-squares estimation function is selected to avoid any unnecessary assumptions of likelihood estimations. The optimal $\boldsymbol{\theta}$ vector is estimated using optimization techniques.

$$ls(\theta) = \sum_{i=1}^{N} [\log\{\mathrm{y_i} - f(\mathrm{x_i}, \widehat{\beta})\}^2\}\text{-}\mathrm{gx_i^{'}}]^2 \tag{4.10}$$

The next step is updating coefficient vector $\widehat{\boldsymbol{\beta}}$, using estimated variance parameters. A new task is added here to generalize the algorithm proposed by Choi and Allen (2009) for the multivariate analysis methods. Updating the predictor variable matrix **X** and the **y** vector is done here before estimating the new $\widehat{\boldsymbol{\beta}}$ vector.

A diagonal weights matrix **V** is obtained using the variance parameters and observations, where $\mathrm{v_{ii}} = \exp(\boldsymbol{\theta}.\mathbf{x}_\mathbf{i}^{'})$. All the data matrices are pre-multiplied by the $\mathbf{V}^{1/2}$ (Neter et al. 1996) and the updated matrices are sent to the PLSR formulation. The optimal $\boldsymbol{\theta}$ vector of the previous step is used as the initial value.

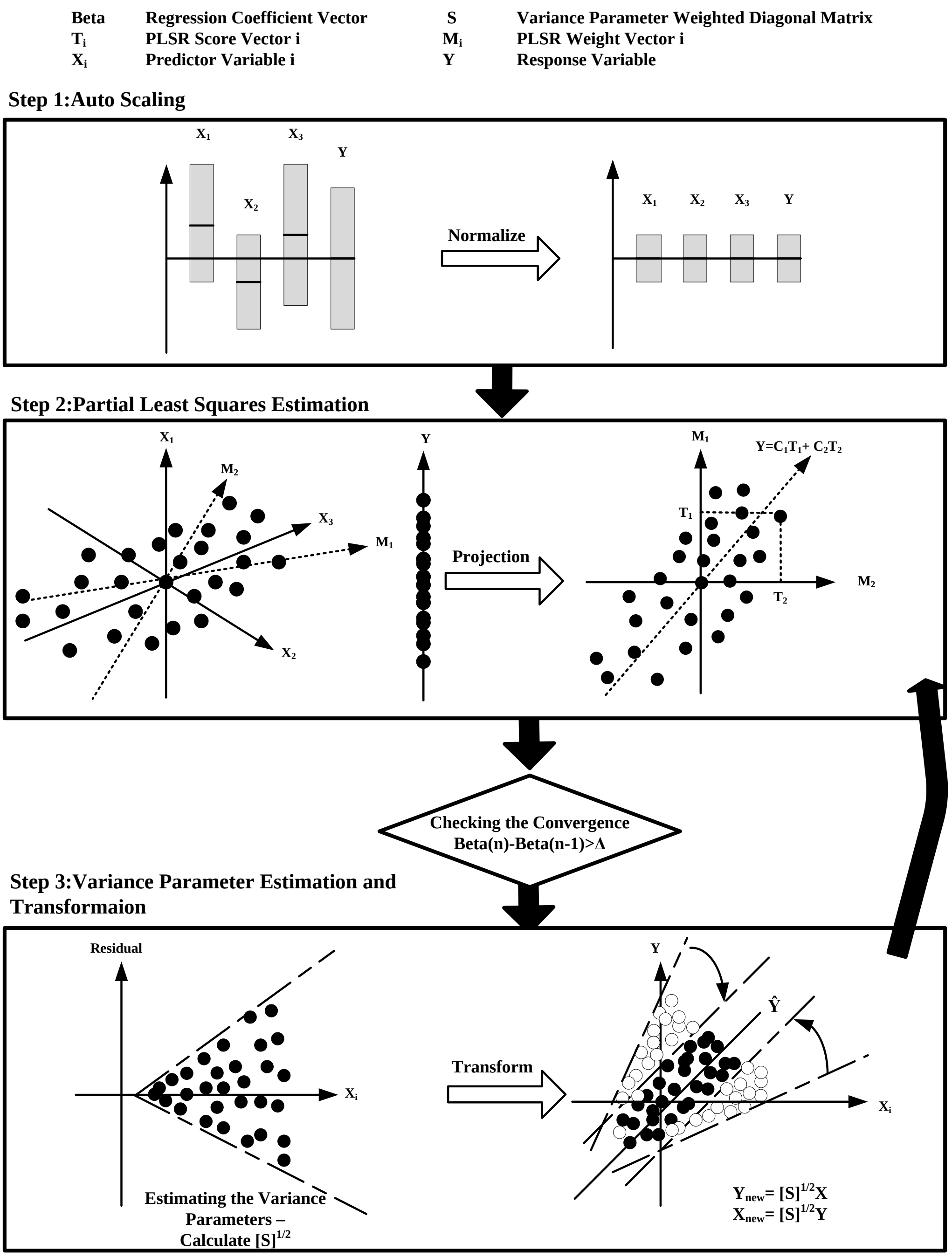

Figure 4-1 Robust Partial Least Squares Regression (PLSR) Procedure

These steps are iterated till $\hat{\boldsymbol{\beta}}_{(n)}$-$\hat{\boldsymbol{\beta}}_{(n-1)}<\Delta$ (the iteration is given by the subscript) till a converged $\hat{\boldsymbol{\beta}}$ vector is obtained. The margin of error for convergence $\boldsymbol{\Delta}$ is set to 0.00001 in a previous study (Choi and Allen 2009), and it is followed in the Robust PLSR formulation process. Finally, the converged coefficient vector is used to generate the predictions, and the optimal variance parameters are kept for the new observation transformation.

4.4 Case Study: Robust Partial Least Squares (PLSR)

The case study was conducted using US automobile market mid and compact size Sedan car models from 2005-2010 to empirically validate the proposed method. In addition, statistical data analysis is conducted at the forefront of the case study to depict the advantages of using PLSR. The car models from 2005-2009 were used for the model formulation and the 2010 data set is kept aside for the validation purposes.

This represents a front-end product concept screening scenario, where designers are using latest available data to formulate a value model. The combined set of data, altogether 132 models, was used for the model formulation. The car models were selected from mid and compact sizes to represent the family car market segment, excluding the high-end luxury cars. According Wassenaar et al. (2005), the customers in this market segment are more aware of the product characteristics and they use product characteristics for the product selection. The most popular cars with reasonable prices were selected for the case study, using the market segment price and demand distributions (see Figure 4-2a). The car models belong to the lower tail<25% of the yearly demand distributions and upper tail>85% of the yearly price distributions were excluded to get an accurate representation of the family Sedan market segment.

The variable selection process is depicted in the Figure 4-2b. The previous case studies from the Sedan market segment (Hoyle et al. 2010; Wassenaar et al. 2003; Wassenaar et al. 2005; Withanage et al. 2012; Withanage et al. 2010b) were used to identify the important product attributes. In addition, the availability of product attribute data from 2005-2010 was considered before the final inclusion to the model. The set of product attributes or **X** variables were selected to represent all the important higher level product characteristics, such as performance, image, comfort and convenience, cost and safety (Hoyle et al. 2010; Withanage et al. 2012). Wheelbase, curb weight, height, displacement, horsepower, torque, city fuel efficiency and highway fuel efficiency were the product attribute selected for the Robust PLSR formulation.

The second order terms (see Equation 2.8) were not considered to minimize the number or variables considered in this pilot study.

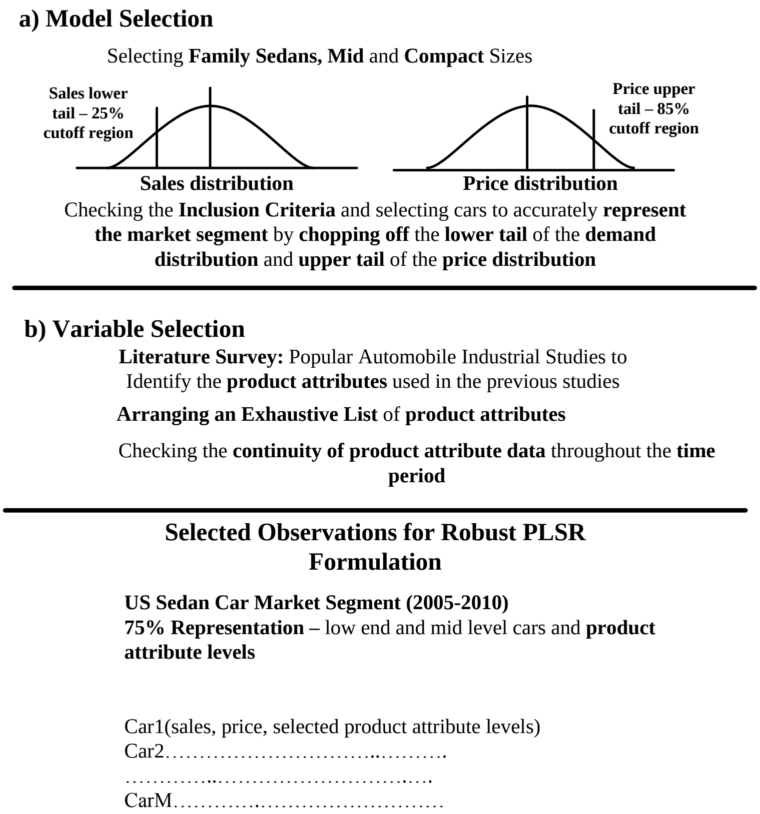

Figure 4-2 Market segment observation and variable screening

CRV, the product value metric, was calculated using the sales, prices, number of competitors and price elasticity for each year. Finally, the ratio of CRVs over the average of the CRVs in each year was taken as the response variable value **y**. Data panels of three years from 2005-2010 were combined to get the training data set for the Robust PLSR model formulation. Also, a comparison study is conducted using 2008, 2009 and 2010 data panels to depict the superiority of PLSR over PCR for the product value-attribute model formulation in this market segment. The **X** variable matrix and **y** vector were auto-scaled at the forefront, and from here onwards those matrices are considered as **X** and **y**. The Robust PLSR algorithm (see Figure 4-3) is used with the tolerance **Δ** set to 0.00001 (Choi and Allen 2009) to estimate the variance parameters and robust coefficient $\hat{\beta}$ vector. The data set aside for validation can be transformed using the variance parameter matrix obtained here. The Robust PLSR coefficients can be used to get the prediction for the validation.

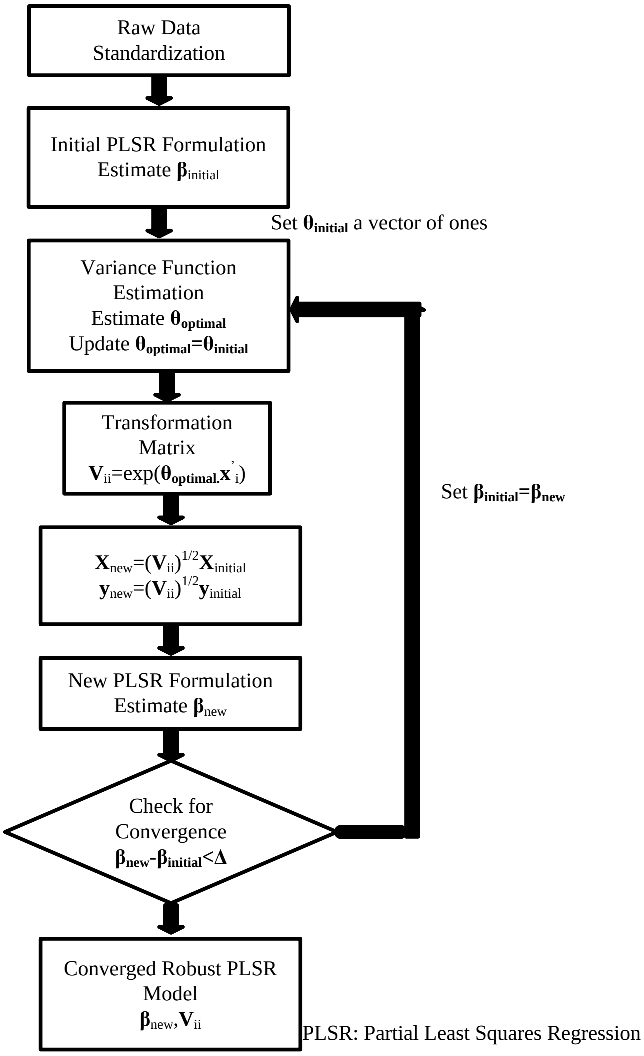

Figure 4-3 Robust Partial Least Squares Regression (PLSR) algorithm

Results

Multicollinearity is a common challenge faced by the analysts dealing with technological product attribute data sets. Therefore, the data set was inspected for the presence of multicollinearity before starting the multivariate analysis. Variance inflation factors (VIF) of the product value-attribute data set was used to check the multicollinearity or the condition. VIF>1 indicates the mild collinearity among variables and VIF>10 indicates extreme collinearity among variables (see Table 4-1a) (Neter et al. 1996). The Sedan market segment product value-attribute data set suffers from extreme multicollinearity, according to these guidelines. PLSR and PCR are the recommended multivariate analysis methods for data sets with high VIF values (Yeniay and Goktas 2002; Carrascal et al. 2009). Therefore, the comparison study is conducted between PLSR and PCR using CRV as the response variable.

Table 4-1 Multicollinearity Inspection Using Variance Inflation Factors (VIF)

	Variance Inflation Factors (VIF)		
Product Attributes	**2008**	**2009**	**2010**
Wheelbase	7.3	10.9	5.7
Curb Weight	14.7	16.5	14.5
Displacement	41.1	71.8	52.4
Horsepower	20.7	33.4	16.6
Torque	47.4	79.1	41.5
City Fuel Efficiency	6.5	18.4	14.8
Highway Fuel Efficiency	3.9	3.4	3.1
Fuel Capacity	5.1	7.9	7.7
Number of Observations	28	27	24

In the comparison study, three model components were formulated to inspect the adjusted R^2 change with the number of components. The adjusted R^2 indicates the amount of **Y** variance explained by a model (Neter et al. 1996). The higher adjusted R^2 values (see Table 4-2a) of 2008, 2009 and 2010 (see Figure 4-4a) PLSR models show the superiority of PLSR with the case study data set. The **X** variance explained given in Table 4-2b can be used to depict the reason for the good model fitting performances of PLSR as compared to PCR (see Figure 4-4). The PCR components (PCA components) are formulated based on the covariance between predictor variables, and they capture the **X** variance efficiently. PLSR components are formulated based on the covariance of the predictor and response variables, and they capture **Y** variance better than PCR (Eriksson et al. 2006). Therefore, PLSR performs better than PCR in providing CRV (**Y**) predictions, in this market segment.

Table 4-2 Variance Explained by Partial Least Squares Regression (PLSR) and Principal Component Regression (PCR)

a)

	Model Component	Y variance Explained (Adjusted R^2) 1	2	3
2008	PLSR	0.7072	0.7906	0.8064
	PCR	0.6905	0.7314	0.7713
2009	PLSR	0.8327	0.8906	0.8947
	PCR	0.8188	0.8863	0.8813
2010	PLSR	0.8083	0.8422	0.8572
	PCR	0.8006	0.8303	0.8285

b)

	Model Component	X Variance Explained 1	2	3
2008	PLSR	0.8158	0.8904	0.9410
	PCR	0.8165	0.9003	0.9475
2009	PLSR	0.8392	0.9218	0.9422
	PCR	0.8398	0.9223	0.9524
2010	PLSR	0.8509	0.9281	0.9522
	PCR	0.8512	0.9301	0.9623

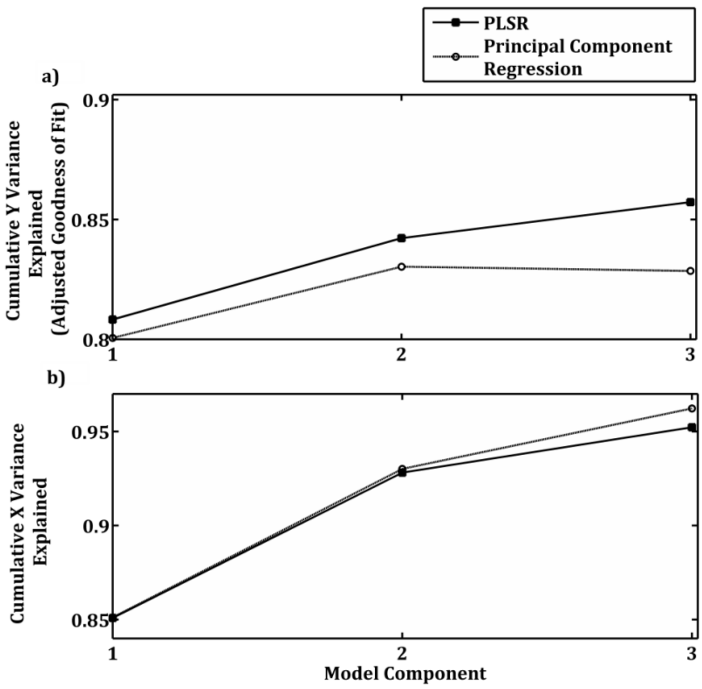

Figure 4-4 Variance Explained by Partial Least Squares Regression (PLSR) and Principal Component Regression (PCR) 2010 Models

The heteroscedasticity of the data was checked at the forefront, before using the Robust PLSR modeling method. One of the most popular standard tests for heteroscedascity, White's test (White 1980; Cameron and Trivedi 2005), was used to check the heteroscedasticity of the product attributes. The White's test result gave a *p value* of $2.09x10^{-4}$, indicating the significant heteroscedasticity presence in the data. The test results reflected the need for the Robust PLSR, in order to handle the heteroscedasticity. A MATLAB routine was used to get the robust model coefficients and the variance parameters. The initial model parameters and the robust model parameters are given in the Table 4-3.

Table 4-3 Partial Least Squares Regression (PLSR) Coefficients and Variance Parameters (θ)

		Direct PLSR	Robust PLSR	Theta θ
	Intercept	0.00	-0.01	
Product Attribute	Wheelbase	0.22	0.24	0.02
	Curb Weight	0.19	0.19	1.01
	Displacement	0.14	0.12	1.24
	Horsepower	0.18	0.20	-0.91
	Torque	0.14	0.13	-0.03
	City Fuel Efficiency	0.06	0.07	1.01
	Highway Fuel Efficiency	0.13	0.12	-0.21
	Fuel Capacity	0.19	0.19	-0.52

Except for the Curb Weigh and the Fuel Capacity, all other coefficients are different between the robust and the ordinary PLSR models. High variance parameters indicate a higher heteroscedasticity presence in the attribute data. Also, the sign of the parameter decide the increase or decrease of variability along the attribute axis in the sample space. The qualitative improvements of the regression model can be depicted using the properties of the residuals.

The residuals of least squares models are assumed to be normally distributed, and it is also valid for the Partial Least Squares Models. Normality of the residuals shows the quality and the stability of the model. The inter-quartile (QQ) plots of residuals are given in Figure 4-5. Clearly, it can be seen that the direct PLSR residuals are deviating from the normal behaviour at the end of the distribution. The Robust PLSR residuals are more evenly distributed around the standard normal line.

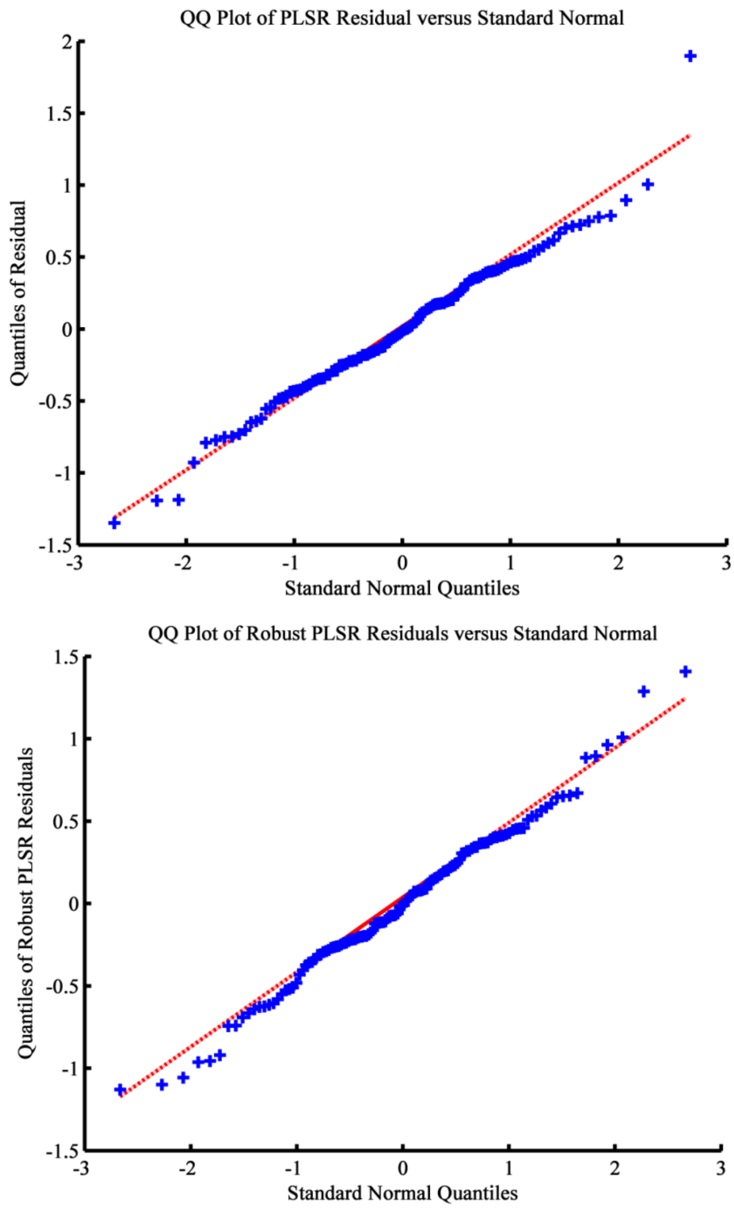

Figure 4-5 Inter-Quartile (QQ-Plot) Plots of Robust and normal Partial Least Squares Regression (PLSR) residuals

In addition to the visualisation, quantitative tests can be conducted to test the normality of the residuals. The Jarque-Bera test (Jarque and Bera 1987) was conducted to check the normality of residuals, due to the small sample size. Given a data set this method test the null hypothesis, that the sample in data vector comes from a normal distribution with unknown mean and variance, against the alternative that it does not come from a normal distribution. The ordinary PLSR failed the test with a *p value* of *0.0220*. The Robust PLSR received a *p value* greater than 0.5. Hence, it is evident that the Robust PLSR algorithm improves the model quality and preserves the basic assumptions. The robust algorithm is a new addition to the family of Partial Least Squares Multivariate Analysis methods.

Discussion

VIF values and the result of White's test confirmed the suspicion about the presence of multicollinearity and heteroscedasticity in the case study data set. According to the comparison study results, PLSR performs better than PCR with the Sedan car product value-attribute data. Aggregation of the four years of product market segment data into one data panel can be identified as the main reason for the heteroscedasticity of error variances. Therefore, similar to an experiment conducted with repetitions, most of the car model series are repeated throughout the time period 2005-2009.

The car model series generate different CRVs in different years due to change of sales and prices, but most of the times the attribute values remains unchanged, due to the long re-styling cycle times. Hence, at one point of the sample space, there are few CRV observations. In addition, the change within a car series is different from each and every car model series, making things more complicated and introducing heteroscedasticity.

However, the observation aggregation is the only alternative for products without adequate historical observations to formulate a reasonable model, which can at least represent the average levels of the preferences. Hence, the proposed method to remove the effects of heteroscedasticity is important for the design decision makers to reduce the model uncertainty originated by the model variance assumption violation.

Theta (**θ**) or the variance parameter value indicates the degree of the heteroscedasticity along the variable (see Table 4-3). The highest positive values were given by the displacement, curb weight, and fuel efficiency. The highest negative value was given by the city fuel efficiency. Manily, positive and negativeness depends on the "megaphone shape" (Neter et al. 1996), the increase or decrease of variance along the sample space.

The highest change in coefficients is 0.02 in many attributes, but the qualitative change of residuals is a proof for the effectiveness of the method. The QQ plot of residuals without the robust algorithm shows the residuals are tilted in clockwise direction, around the centre of the normal line (see Figure 4-5). Also, the skewness is increased along the residual line and finally the residuals are falling away from the normal line substantially. On the other hand, the Robust PLSR residuals are more balanced and closely following the normal line.

Although, the visual methods are one of the ways to show the advantages, quantitative methods are used as standard validation methods. The normality test results further confirmed the positive effect of the Robust PLSR algorithm, by probabilistically validating the normality of residuals. Normality of residuals and their even spread (homoscedasticity) is an unwritten, basic assumption of any least square estimation related regression modeling method. Therefore, the introduced robust algorithm can be implemented in similar situations to obtain PLSR models, which are robust to the heteroscedasticity.

4.5 Closure

The fundamental component of the Strategic Decision Support Framework, the static modeling method, is presented in this chapter. The two novel modeling approaches, the value meta-model and the robust modeling algorithm, are the main contributions introduced to address the statistical errors in value modeling. The value meta-model is used to formulate a multivariate model to represent the product value-attribute relationship in a product market segment. The product attributes (a quadratic function) are used as the predictor variables and CRVs are used as the response variables in the model formulation process. The value meta-model is proposed as a decision support tool in the front-end conceptual product screening process.

The value meta-model or the simplified value curves can be used to model the product value-attribute relationship using PLSR method. The price-endogenity is removed from the product value-attribute model by modeling the pure characteristic values of products. Hence, the attribute-price trade-off is not effecting the model predictions. Product prices are represented in the perceived value of product, given by the CRVs. Furthermore, the exogenous and endogenous factors influencing the market segment are introduced to the model by the CRV, which is a function of the product demands, prices and price elasticity.

The proposed Robust PLSR is a new addition to the Partial Least Squares family. It is based on the variance parameter estimation methods and it transforms the variable space to minimize the heteroscedasticity present in the data. This algorithm needs the variance parameters to be estimated at the forefront. Hence, using it inside a dynamic model is questionable. However, the robust algorithm can be used in situations, where designers are combining data panels and formulating static models.

Chapter 4 addressed the first research question by providing a robust static model to estimate the product value-attribute relationship in a technological product market segment. The model uncertainties due to the shortcomings of design data and value modeling approaches are the research gaps targeted here. Chapter 5 takes the research study one step closer to the ultimate research objective by removing the unrealistic assumption of time invariant customer preferences from the product value-attribute modeling process. It addresses the research gap due to the absence of dynamic preference models in the currently used front-end decision support methods.

5 DYNAMIC VALUE-ATTRIBUTE MODELING

5.1 Dynamic Partial Least Squares Regression (PLSR) for the Front-End Strategic Decision Support

The Dynamic PLSR model is the first strategic decision support tool introduced in this thesis. The dynamic model formulation is presented in this chapter with a case study for the empirical performance validation.

The dynamic product value-attribute modeling is proposed in this thesis to reduce the model uncertainty, caused by the dynamic customer preferences. Customer preferences are varying with time (see Figure 5-1) as pointed out in previous research studies (Monczka et al. 2009). Currently, static models are used for the product value-attribute modeling process. Therefore, the model uncertainty can be increased by the over simplification of customer preferences. The proposed dynamic product value-attribute relationship supports the PDD decision makers to take strategic decisions with reduced risks, by incorporating the dynamic customer preferences in the front-end product concept screening process.

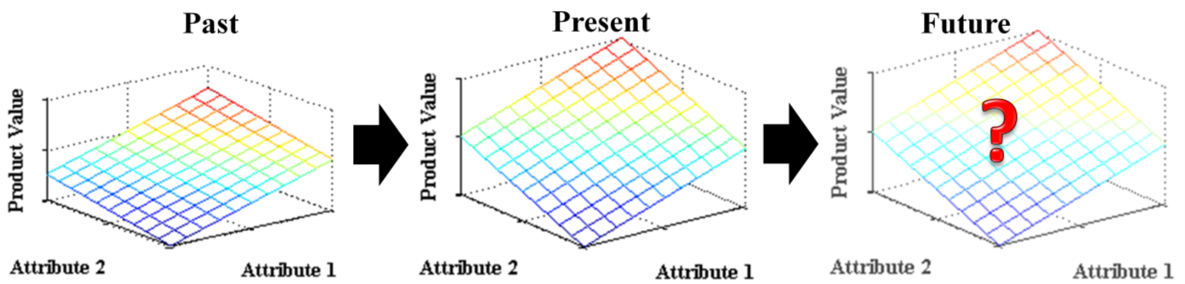

Figure 5-1 The future product value-attribute relationship prediction

In Chapter 4, the novel static value modeling approach, the value meta-model, was introduced with the theoretical derivation. It is derived using the value curves; a micro-economic value modeling method introduced by Cook et al. (1994).The next challenge is extending this product value-attribute relationship from a static model to a dynamic model to represent the real market behaviour or the dynamic customer preferences. In this chapter a novel Dynamic Revealed Value Model (RVM) is introduced as the solution to this problem (Withanage et al. 2010b). Basically, the underlying model is a Dynamic PLSR model. The Dynamic PLSR is the third main contribution of the thesis.

The conceptual products are going to be released to the future markets, due to the concept-to-customer lead time (see Figure 3-1). Thus, design decision makers are more interested in the future product value-attribute relationship to find the best product concepts for the future markets. In the proposed modeling approach, the time series forecasting techniques are used to capture the time series properties such as levels, trends and cyclical patterns of the product value-attribute model parameters. Eventually, these properties are used to forecast the future model parameters to formulate the future product value-attribute relationships, considering the concept-to-customer lead time.

5.2 A Novel Decision Support Framework for the Value Driven Design

A four step methodology is presented in this section covering the procedure of the Strategic Decision Support Framework formulation. The first decision support tool of the proposed framework, the dynamic value-attribute model, is formulated by combining the time series forecasting algorithms and PLSR.

The proposed Strategic Decision Support Framework formulation is consisted of four main steps (see Figure 5-2). CRV, the perceived value of products, is estimated in Step 1 with given market segment data. It is used as the response variable for the RVM estimation. The product value-attributes relationship, RVM, is estimated in the Step 2 using the estimated CRV and the corresponding product attribute data. PLSR is used for the RVM estimation and static RVMs are formulated at the each historical time frame. The model parameters are arranged into a time series, and used as the time series observations for the model projection.

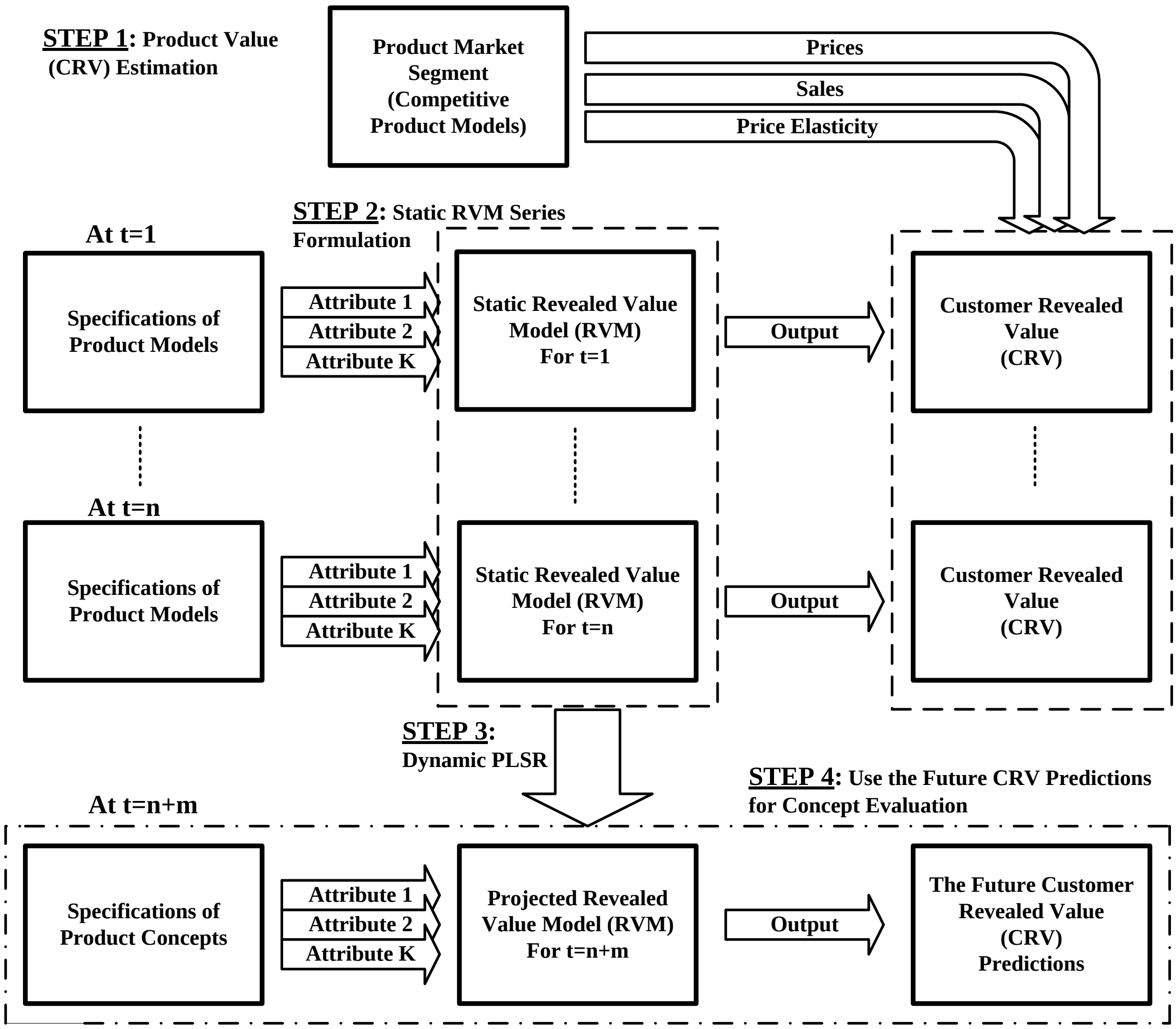

Figure 5-2 Overview of the dynamic value-attribute relationship based Strategic Decision Support Framework (Withanage et al. 2010b)

Dynamic PLSR modeling method is used in Step 3 to project the static RVM parameter series to formulate the future RVMs. Finally, in the Step 4, designers may use the projected future RVMs to select the best product concepts, in order to address the future product value-attribute relationships. In this thesis, more attention is paid to the product concept screening process, instead of other front-end design decision making activities. The additional data requirements of the concept generation process, including design and manufacturing constraints, are the main reason for only focusing on the product concept screening process. The four step procedure is briefly described in the following paragraphs.

Step1: Product value estimation using the market segment data

The first step towards the customer driven strategic product planning is obtaining a measurement of the perceived value of products. Value and utility have been used in various engineering design problems to evaluate the usefulness of a concept (Fernandez et al. 2005; Simpson 1998; Antonsson and Otto 1995; Thevenot et al. 2007). Hence, the maximization of CRV will ensure achieving higher levels of customer satisfaction. CRV (Donndelinger and Cook 1997;Cook and Kolli 1994; Cook and Wissmann 2007) is estimated using sales, prices and price elasticity of the selected product market segment.

Step 2: Formulating historical static RVM series

In this step, the earlier introduced soft modeling technique, PLSR, is used to formulate the RVMs. A RVM represents the value-attribute meta-model introduced in the previous chapter. Simply, it is a functional relationship between the product attributes and overall product value (i.e., CRV).

As an example, in case of a passenger vehicle design, the RVM is based on attributes of the vehicles, such as fuel consumption, power, handling, cabin space, etc., and the CRV obtained at the Step 1. The static RVM series was obtained in this step by formulating RVMs at each and every historical time frame.

Step 3: Dynamic RVM for the future RVM projection

The next step is to predict future RVMs based on the series of static RVMs obtained in the Step 2 using time series forecasting algorithms. This prediction estimates the evolution of the value-attribute relationship. Finally, the dynamic RVM is obtained using this approach. The dynamic RVM method is a hybrid modeling method, consisting of a time series forecast technique and the historical static RVM parameters formed in the Step 2. The dynamic model is formulated using the optimum PLSR components of a given future time frame, which are obtained by minimizing forecasting and model formulation errors. The model formulation error term is obtained using the inherent structural properties of the PLSR model parameters. The Dynamic RVM formulation process is discussed in the next section.

Step 4: Using the future RVMs for concept evaluation

Mainly, two types of decision making can be seen in the PDD process. The first one is selection decision-making. At the front-end of PDD process, there may be a number of different product concepts. However, design decision makers (product developers) need to select the best one to be further developed as the final product. This process is critically important, since the product concept will decide the most of the characteristics of the final product. The dynamic RVM established in Step 3 is employed to select the most promising product concept at the targeted time of market introduction.

Also, the concept generation or finding right combination of product attributes in presence of multiple conflicting goals is an important design decision making task. However, the presented thesis is focused on the front-end product concept screening, as explained earlier. Dynamic RVM is empirically validated using a case study from the US sedan market segment.

5.3 Dynamic Revealed Value Model (RVM) Formulation

Dynamic RVM is the ultimate result of an optimization process, which combines the PLSR and time series forecasting algorithms. In this dynamic modeling method, all historical static RVM parameters (PLSR models in this case) are used to generate forecasts of future model parameters. However, a tightly controlled forecasting method is used to ensure the structural validity of the future models, unlike to the dynamic model of Kim et al. (2005). This unique modeling method is illustrated in Figure 5-3.

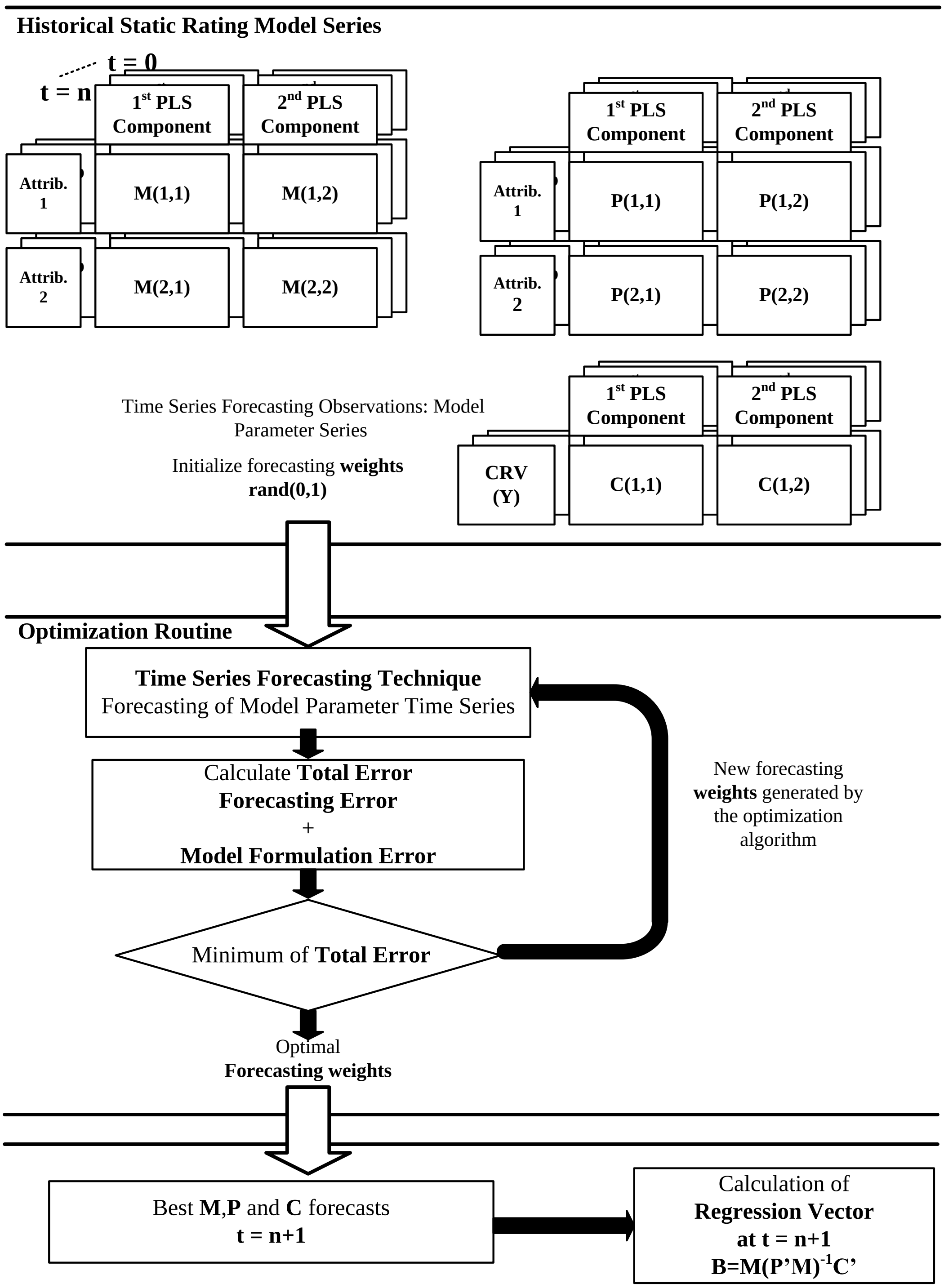

Figure 5-3 Overall procedure of the Dynamic Revealed Value Modeling (RVM) (Withanage et al. 2010b)

The first task in formulating a Dynamic RVM is estimating the model parameters of historical static models. The regression coefficient, **B,** contains important information about the relationship between product attributes (**X**) and CRV (**Y**). In order to obtain the future value-attribute relationship, **B** is projected to a given future time frame using the historical model parameter observation series.

As given in Equation 2.21, the regression vector **B** is formed by linear algebraic operations of **M**, **P** and **C** matrices. Each and every element in **M**, **P** and **C** matrices can be forecasted using statistical time series forecasting methods. However, DES forecasting technique (Chopra and Meindl 2001; De Lurgio 1998) was opted in the presented case study to capture the levels and trends of the elements, due to the limited availability of historical data. Advanced statistical time series forecasting techniques (see Section 2.5) such as ARIMA (Newbold 1983) can be used to get more accurate results, with the availability of more data. The algorithm of the DES forecasting technique is given in Equation 5.1 -5.2.

$$b_t = \gamma(S_t + S_{t-1}) + (1-\gamma)b_{t-1} \qquad 5.1$$

Where, α and γ are the optimal weights of DES technique to be found for to get the minimal total errors, using an optimization routine. Initial values are given by $S_1=Y_1$ and $b_1=Y_2-Y_1$, where Y_i is the real observation (i.e., elements in **M**, **P**, and **C** model parameters matrices) of the i^{th} year. The forecasts are obtained for an m steps ahead time frame by the equation given below.

$$F_{t+m} = S_t + mb_t \qquad 5.2$$

All errors associated with forecasting and model structural properties are combined to get the objective function of the optimization process of estimating the best weights for the forecasting algorithm. This will ensure a structurally sound future model, which represents the future market scenarios more accurately. The objective function formulation, with the DES technique selected for the case study, is given in Table 5-1. Any other time series forecasting technique can be plugged into replace the DES Forecasting technique, into the optimization objective function formulation, as explained earlier.

Table 5-1 Total Error Formulation (Withanage et al. 2010b)

V common notation used for **P**, **M** and **C** matrices

$\mathbf{V}[a]$ column a from matrix **V**

$\mathbf{V}[k,a]$ value of the k^{th} variable loading/weight/coefficeint regarding to PLS component a

$F^{t}_{\mathbf{V}[k,a]}$ forecast of the $\mathbf{V}[k,a]$ element at time t $Y^{t}_{\mathbf{V}[k,a]}$ real value (observation)

C the $(1\times A)$ **Y** weight matrix since only one **Y** variable in RVM

DES Forecasting

$$F^{t+m}_{\mathbf{V}[k,a]} = S^{t}_{\mathbf{V}[k,a]} + m\, b^{t}_{\mathbf{V}[k,a]} \quad // m = 1 \text{ for one year ahead forecast}$$

$$S^{t}_{\mathbf{V}[k,a]} = \alpha_{\mathbf{V}[k,a]} Y^{t}_{\mathbf{V}[k,a]} + (1-\alpha_{\mathbf{V}[k,a]})(S^{t-1}_{\mathbf{V}[k,a]} + b^{t-1}_{\mathbf{V}[k,a]})$$

$$b^{t}_{\mathbf{V}[k,a]} = \gamma_{\mathbf{V}[k,a]}(S^{t}_{\mathbf{V}[k,a]} + S^{t-1}_{\mathbf{V}[k,a]}) + (1-\gamma_{\mathbf{V}[k,a]}) b^{t-1}_{\mathbf{V}[k,a]}$$

Errors in PLS Model Formulation

$$\varepsilon_{\text{Model Formulation}} = \sum_{a=1}^{A}\{1-|(F^{t+m}_{\mathbf{M}[a]}{}' F^{t+m}_{\mathbf{M}[a]})|\} + \sum_{a=1}^{A}\{1-|(F^{t+m}_{\mathbf{M}[a]}{}' F^{t+m}_{\mathbf{P}[a]})|\} + \sum_{a_1=1}^{A}\sum_{a_2=1}^{A}|(F^{t+m}_{\mathbf{M}[a_1]}{}' F^{t+m}_{\mathbf{M}[a_2]})| + \sum_{a_3=1}^{A}\sum_{a_4=1}^{A}|(F^{t+m}_{\mathbf{P}[a_3]}{}' F^{t+m}_{\mathbf{M}[a_4]})| \quad //$$

$$a_1 \neq a_2,\ a_3 > a_4\ \&\ a_3 \neq a_4$$

$\because$ Properties of columns of **M** and **P** matrice

s

Error Sum of Squares for Forecasting

$$\varepsilon_{\text{Forecasting}} = \sum_{k=1}^{K}\sum_{a=1}^{A}\sum_{t=1}^{n}\{(F^{t}_{\mathbf{M}[k,a]} - Y^{t}_{\mathbf{M}[k,a]})^2 + (F^{t}_{\mathbf{P}[k,a]} - Y^{t}_{\mathbf{P}[k,a]})^2 + (F^{t}_{\mathbf{C}[1,a]} - Y^{t}_{\mathbf{C}[1,a]})^2\}$$

Objective Function $\varepsilon_{\text{Total}} = \varepsilon_{\text{Model Formulation}} + \varepsilon_{\text{Forecasting}}$

There are two types of errors in the dynamic RVM formulation as shown in the Table 5-1. Minimization of the model formulation error ensures the preservation of the orthonormal and orthogonal inherent properties of **M** and **P** components ensured by NIPALS algorithm. The first property is that columns of **M** forms an orthonormal set. This means the columns of **M** are orthogonal to each other (i.e., $\mathbf{m}_a'\mathbf{m}_b$=0 where a≠b), and their norm is unity (i.e., $\mathbf{m}_a'\mathbf{m}_a$=1). The second property is interactions of **M** and **P** columns should satisfy $\mathbf{m}_a'\mathbf{p}_a$=1 and $\mathbf{p}_b'\mathbf{m}_a$=0, where b>a. The forecasted RVM is formulated using the optimal forecasting weights to satisfy these properties (Withanage et al. 2010b). The deviations from these properties are formed as the RVM formulation error.

Table 5-2 Optimization problem formulation (Withanage et al. 2010b)

$\mathbf{V}[k,a]$ value of the k^{th} variable loading/weight/coefficeint regarding to PLS component a

Given : $\mathbf{M}, \mathbf{P}$ and $\mathbf{C}$ from $t=0$ to $t=n$

Find : $\alpha_{\mathbf{M}[k,a]}, \gamma_{\mathbf{M}[k,a]}, \alpha_{\mathbf{P}[k,a]}, \gamma_{\mathbf{P}[k,a]}, \alpha_{\mathbf{C}[1,a]}, \gamma_{\mathbf{C}[1,a]}$

Satisfy : $0<\alpha_{\mathbf{M}[k,a]}<1$ $\quad 0<\gamma_{\mathbf{M}[k,a]}<1$

$0<\alpha_{\mathbf{P}[k,a]}<1$ $\quad 0<\gamma_{\mathbf{P}[k,a]}<1$

$0<\alpha_{\mathbf{C}[1,a]}<1$ $\quad 0<\gamma_{\mathbf{C}[1,a]}<1$

Minimize : $\varepsilon_{\mathbf{Total}}(\alpha_{\mathbf{M}[k,a]}, \gamma_{\mathbf{M}[k,a]}, \alpha_{\mathbf{P}[k,a]}, \gamma_{\mathbf{P}[k,a]}, \alpha_{\mathbf{C}[1,a]}, \gamma_{\mathbf{C}[1,a]})$ // total error function

Another type of errors is in forecasting the elements of **M**, **P** and **C** matrices. The forecasting error is calculated by comparing forecasts with real observations of the elements. In the presented case study, error sum of squares was used for the objective function. More parameters can be added to the objective function to control the optimization process. The errors can be prioritized using weights in front of them to extend this algorithm, according to the needs of the decision makers.

Finally, the optimal weights, α and γ, of each element in **M**, **P**, and **C** should be obtained by minimizing the total error. The future **M**, **P**, and **C** can be established using them. The optimization problem formulation is given in Table 5-2.

5.4 Case Study: Dynamic Product Value-Attribute Modeling

The relatively long product development cycle times of passenger cars make the strategic decision making a critical factor for the successes in the highly competitive Sedan market. As explained in Chapter 3, the compact and mid size Sedan market is one of the ideal markets to implement the strategic decision support framework introduced in this thesis. Currently, the concept selection in the industry more or less relies on decision-makers' experience and skills to forecast the preference shifts (Khan 2002; Downen et al. 2005).

The case study was developed to evaluate passenger vehicle concepts based on historical sales data of the prominent US passenger cars from 1998 to 2008. The passenger car models in this study were selected to represent compact to midsize cars from the US sedan market segment. As mentioned before, in this market segment most of the customers are making rational choices, by selecting cars based on product attribute levels (Wassenaar et al. 2003).

The sales data of the models were acquired through a market research and analysis firm to estimate CRVs. Customer requirements and their expectations may be understood by analyzing revealed values of car series. The product attribute data of the vehicles were obtained from technical specifications listed in Edmunds* website. Due to the limitation of the sales data, sales of each model was considered as the sales of an average trim level (attribute values in the mean range), in order to tally the levels of attributes with revealed values.

Case Study Scenarios

The case study consists of two specially formulated scenarios (Withanage et al. 2010b). In Scenario 1, 2008 vehicle models were assumed to be the product concepts going through the screening process. In this scenario, CRVs of 2008 car models were predicted from 3 different time horizons; namely one year ahead forecasts from 2007, two years ahead forecasts from

2006 and three years ahead forecasts from 2005. Finally, forecasting errors were calculated using 2008 observations for the validation of the dynamic model.

In Scenario 2, completely new car model values were generated and checked to assess the dynamic model predictions. This shows one of the main strengths of the proposed approach, because existing forecasting techniques cannot be used to forecast values of completely new products. Two new vehicle models, just introduced to the US market in 2006, were assumed as new product concepts in 2005. The future CRVs of these two product concepts were estimated for 2006-2008, in order to depict the strengths of the proposed framework. The efficiency and effectiveness of the proposed framework were validated by comparing the real and forecasted values.

Dynamic Revealed Value Model (RVM) Formulation

In this sub section, the procedure followed to formulate the proposed framework, using real market data, is given in detail. The four step methodology given in Figure 4-2 was followed to formulate a Dynamic RVM. The data from 1998-2007 were used for predicting the CRVs of 2008 as given in the figure. More descriptions about the tasks done inside each step are given below.

Step 1: From the passenger car sales data, CRVs were calculated by setting the automobile price elasticity as unity, according to Donndelinger and Cook (1997).

Step 2: The CRVs calculated in Step 1 were converted to base ten logarithms and used as the Y block, the response variable values. The selected 11 attributes and their quadratic values (see Table 5-3) are auto-scaled and considered as the **X** block, the predictor variable values.

All variable values were auto-scaled within -1 and +1; therefore, units of the variables do not affect the PLSR modeling due to the auto-scaling. A static RVM was formed in each year from 1998 to 2008 using the PLSR. The static RVM of 2008 is kept for the validation purpose.

Table 5-3 X and Y block variable formation for the product value-attribute modeling

Block	Variables	
X block	Horse power Curb weight Torque Fuel efficiency Wheel base Engine Height Length Cabin volume Ground clearance Width	first order and quadratic terms
Y block	**Log_{10} (Customer Revealed Value)**	

The goodness of fit (R^2) and goodness of prediction (Q^2) of the static RVMs were estimated for the internal validation. Table 5-4 shows the internal validation results. In general, Q^2 >0.5 is the rule of thumb to consider that a RVM is sufficiently accurate for prediction (Eriksson et al. 2006). All RVMs are healthy except those of 1998, 1999 and 2006. Only, the 2006 R^2 is less than 0.60, which shows the fit of the value-attribute meta model with the real market observations. Hence, the models of other years are also in the healthy region (Eriksson et al. 2006).

Step 3: Time series of **M**, **P** and **C** in 1998-2008 were obtained from the static RVMs formed in Step 2. The **M** and **P** elements are predicted to formulate a Dynamic RVM, capturing the time series variations and preserving the inherent properties of the future RVM based on the optimization algorithm illustrated in Figure 5-3.

Table 5-4 Goodness of fit and goodness of prediction values of the static Revealed Value Model (RVM) series

Year	*Goodness Of Fit* R^2	*Goodness Of Prediction* Q^2
1998	0.6	0.44
1999	0.65	0.48
2000	0.68	0.54
2001	0.7	0.57
2002	0.79	0.72
2003	0.76	0.69
2004	0.69	0.59
2005	0.72	0.64
2006	0.51	0.37
2007	0.65	0.59
2008	0.71	0.61

Three future RVMs were projected using the static RVMs of 1998-2007 (one year ahead), 1998-2006 (two years ahead) and 1998-2005 (three years ahead). The direct search algorithm (Kolda et al. 2006) in MATLAB optimization toolbox is used to find the optimal forecasting weights to formulate a Dynamic RVM in this process.

Step 4: Based on the two scenarios described in Section 5.4.1, validity of the Dynamic RVMs obtained in Step 3 were investigated using the CRV predictions. The results of this study are discussed in the next section.

Results

Scenario 1

This scenario was developed to represent the decision making task of selecting the best concept with the highest forecasted CRV for the future market. The Mean Absolute Percentage Error (MAPE) was used to validate the Dynamic RVM method by comparing CRV forecasts with CRV direct estimates.

The accuracy of the prediction by the proposed method is good even though the length of the observations series was limited, as shown in Figure 5-4. Losing the significance of the results (higher MAPE value) due to the increased forecasting horizon is a natural trend. The low MAPE values reflect the accuracy of the proposed method in forecasting CRVs of product concepts. Hence, proposed method can be used to support the front-end product concept screening process. The CRV time series plots of only five sedan models continuing from 1998 to 2008, are illustrated in Figure 5-5. Despite the limited span of data (i.e, eight data sets for three year ahead forecast), the obtained Dynamic RVM provides spot on forecasts in two occasions.

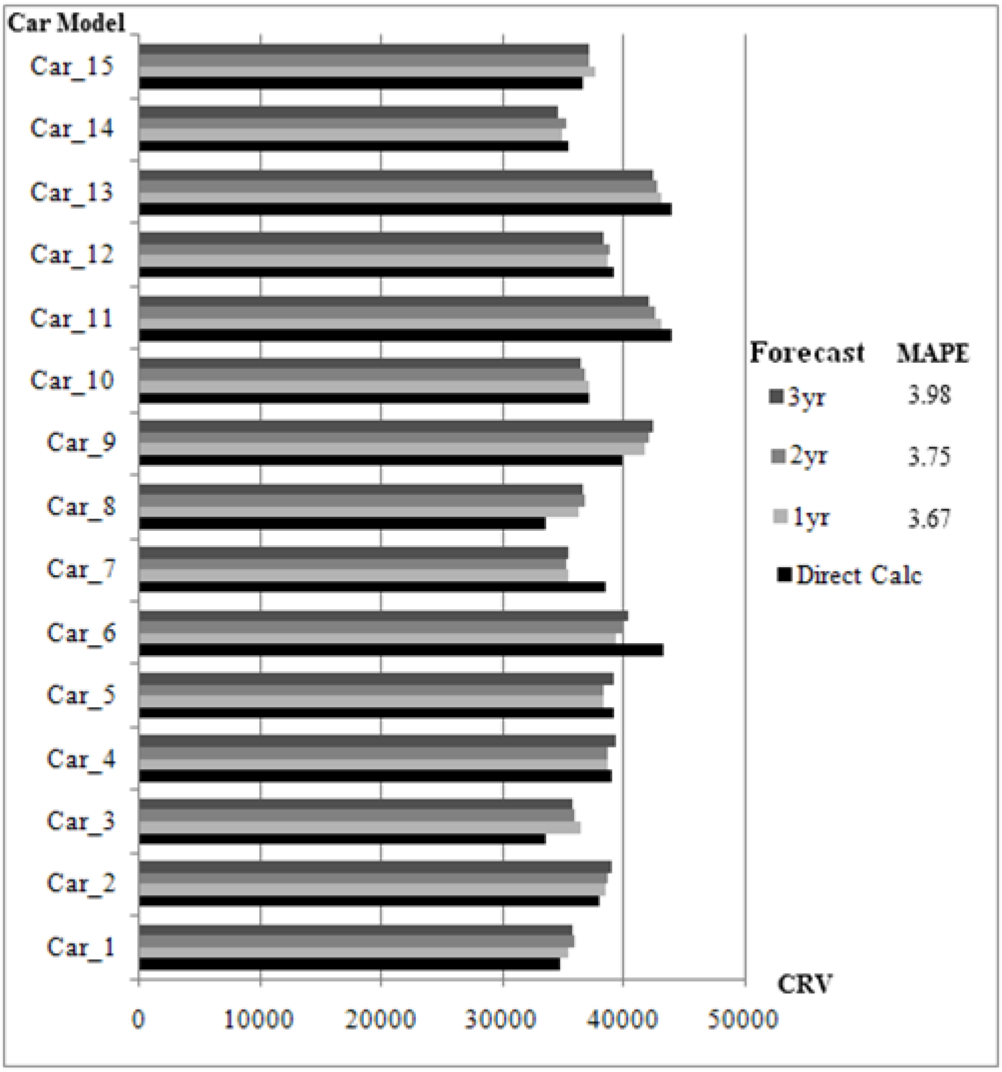

Figure 5-4 Three year ahead Customer Revealed Value (CRV) forecasts (Withanage et al. 2010b)

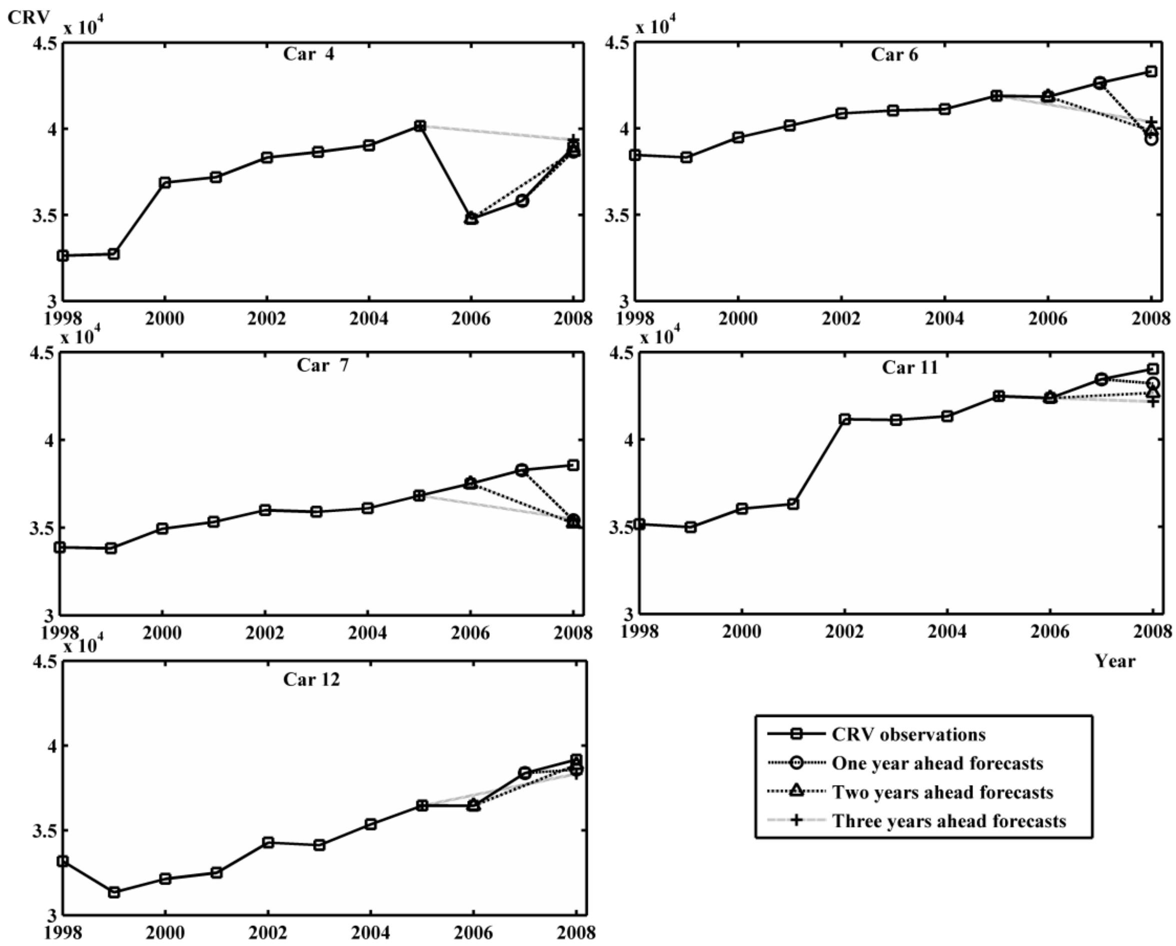

Figure 5-5 Customer Revealed Value (CRV) time series (Withanage et al. 2010b)

Car series from various brands were selected to generalize the analysis, and to represent the market segment accurately. The brand power is not considered due to the product value-attribute nature of the case study. It can be the source of the high MAPE values. Cars with high brand power and low attribute levels are generating negative errors (Car_6 and Car_7 in the Figure 5-5). Cars with high product attribute levels and low brand power are generating positive errors (Car_8 and Car_9). The newly introduced car model, Car_3, suffers a setback due to the unfamiliarity to the market segment and it does not perform as expected. The prediction errors are analysed in the case study Discussion section.

Scenario 2

In Scenario 2, Car_2 and Car_7 were assumed to be the new concept candidates, which are going through the evaluation process. It is a reasonable assumption since Car_2 was introduced to the US market in late 2005 and Car_7 completely redesigned and released to the market in 2006.

In this scenario, Dynamic RVM was formulated using 1998 to 2005 sales data. This scenario mimics the completely new product introductions, where the industry is currently heavily depending upon the experience of the decision makers. The proposed method can support the decision makers by providing forecasts.

Forecasting results of the new vehicle series are given in Figure 5-6. The results are good for the Car_2 but questionable for the Car_7. The reason for the large error generated by Car_7 is the brand power effect, as explained in Scenario 1.

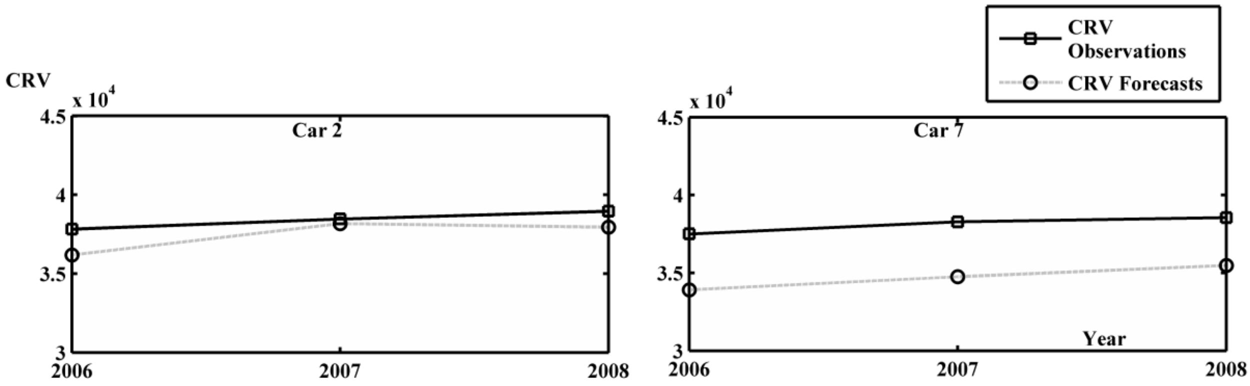

Figure 5-6 New car series Customer Revealed Value (CRV) observations and forecasts

Discussion

In the results of the PDD decision making scenarios, high errors were observed in some car series. High error values are due to brand power effects, which cannot be captured by the proposed approach. In order to show the relationship between the errors and the brand rating, the brand ratings of year 2008 given by Consumer Report Organization are employed.

As shown in Table 5-5, the amount of errors, (error = directly calculated CRV from 2008 sale data - 1 year head predicted CRV) are related to the 2008 brand rating. The correlation between the brand rating and the error term is 0.82.

The error in Car_3 can be attributed to its newness to the market (i.e., lack of product image and unfamiliarity). Removing Car_3 from the above calculation, correlation increases to 0.99, which is a clear indication of the strong relationship.

Table 5-5 Errors in predictions and brand ratings of the high error generating 2008 car models

Model	Direct Calc	1 year	Error	2008 Brand Rating
Car_3	33535	36495	-2960	57
Car_6	43292	39383	3909	78
Car_7	38555	35417	3138	78
Car_8	33535	36351	-2816	70
Car_9	39821	41821	-2000	70

In addition, the 2008 static RVM (the model formulated with 2008 market segment data) and 2008 projected RVM are compared in Table 5-6 to validate the results. Significantly low error margins of CRVs between 2008 RVM predictions and the projected 2008 RVM forecasts clearly show the effectiveness of the proposed method. This implies that in the RVM formulation process the brand power effects are filtered out from the product value-attribute relationship. Furthermore, the rankings of the leading 2008 product concepts (first five) of these two models are exactly matching with each other. In the proposed framework, the CRV rankings are used to select the best product concepts for the future market segment. Therefore, the CRV rankings given in Table 5-6 further confirm the usability of the proposed framework as a decision support method in the front-end product concept screening process.

As mentioned earlier, the main objective of this study is to support the front-end concept screening of a manufacturing organization. Thus, due to the filtering out the brand power and other unwanted marketing effects in the model formulation, Dynamic RVMs only contain the engineering attribute effects which are important for the product value-attribute relationship. This serves well the purpose of the front-end product concept screening process in a manufacturing firm, because any chosen product concept will be manufactured under the same brand. Hence product concepts should be considered to have the same level of brand power, when they are evaluated.

Table 5-6 Customer Revealed Value (CRV) predictions of the real and projected Revealed Value Models (RVM)

	2008 Real RVM		2008 Projected RVM		
Model	**CRV Predictions**	**Rank**	**CRV Forecasts**	**Rank**	**Average Percentage Error**
Car_11	43813	1	43194	1	1.41
Car_13	43605	2	43178	2	0.98
Car_9	41897	3	41821	3	0.18
Car_6	39791	4	39383	4	1.03
Car_4	39092	5	38673	5	1.07
Car_2	38845	6	38491	7	0.91
Car_5	38721	7	38264	8	1.18
Car_12	37623	8	38585	6	2.56
Car_15	37177	9	37644	9	1.26
Car_10	37019	10	37128	10	0.29
Car_8	36641	11	36351	12	0.79
Car_3	35928	12	36495	11	1.58
Car_7	35642	13	35417	14	0.63
Car_1	35170	14	35455	13	0.81
Car_14	34328	15	34941	15	1.79
				MAPE	**1.10**

5.5 Closure

A novel framework to evaluate multiple conceptual models, using a Dynamic RVM, is proposed as the solution to the second research question (RQ2). The proposed method is a time saving approach compared with the traditional methods, such as quality function deployment and conjoint analysis. Instead of depending upon survey data, the proposed dynamic model can be formulated with the readily available sales and attribute values of products.

A novel Dynamic PLSR algorithm, the main decision support tool of the proposed framework, is introduced in this chapter. An optimization routine is embedded in this algorithm to control the model parameter forecasts using model structural errors and forecasting errors. Dynamic RVMs are formulated using the Dynamic PLSR algorithm. This enables forecasting structurally sound future RVMs at tentative product launch time, considering the effect of concept-to-customer lead times.

Mainly, the proposed Dynamic PLSR modeling method addresses the need of dynamic preference models in PDD related decision support activities. The dynamic modeling method is proposed as an alternative method to address the model uncertainty by accurately representing the dynamic preferences in value modeling. Despite of some limitations, such as inability to pick sudden changes, and unable to predict the unusual irrational customer behaviour, it is believed that the proposed method facilitate a strategic decision support framework. This framework is intended to use for the front-end conceptual screening in the context of customer driven product design, in order to satisfy the future customer preferences.

The framework proposed in Chapter 5 only deals with the product value-attribute relationship. The next research question is extending the proposed dynamic product value-attribute modeling method to include the higher level product characteristics, which are closer to the customers. The dynamic PLSPM, presented in next chapter, is proposed as the solution to this problem. It can be used to extend the product value-attribute models by including LVs to represent the higher level product characteristics.

6 DYNAMIC VALUE-CHARACTERISTICS MODELING

6.1 Partial Least Squares Path Modeling (PLSPM) for Product Design and Development (PDD)

In Chapter 5, a dynamic product value-attribute model was introduced for the strategic decision support in the front-end conceptual product screening process. In this chapter, the value-attribute modeling is extended by including a LV layer to represent the higher level product characteristics. In addition to providing better value predictions, this added feature will enable the exploration of the market segment value structure.

Generally, the product value-characteristics relationship governs the product mix and levels of attributes, in customer driven technological product market segments. However, modeling and analysing the value structure is a difficult task, due to limitations of the currently used modeling methods. The Structural Equation Modeling, the mainstream method used for this purpose, is hampered by the higher data requirements and the unrealistic assumptions in the estimation process.

In this thesis, PLSPM is proposed as the solution to overcome the challenges entailed with technological product attribute data. Especially, PLSPM provides robust model parameters, when coupled with PLSR. The strengths of these multivariate analysis models can be effectively used to overcome the shortcomings of technological product attribute data (see Section 2.3).

The first step of understanding product value-characteristic relationship is estimating the overall value of a product. CRV is used as the standard value metric throughout the methods introduced in this thesis. The theoretical definitions and the derivation of the value-attribute meta-model were used for the theoretical structural validation of RVMs and use of CRV as the value metric. Furthermore, use of CRV as a value metric can be empirically validated using exploratory abilities of PLSPM. Two analyses were conducted using the US Sedan market data to validate the use of CRV (Withanage et al. 2011) and the value modeling approach proposed in this thesis. These two concepts of proof studies reinforced the validity of the proposed approach by providing empirical proofs.

The following sections of this chapter are dedicated to the formulation of the dynamic product value-characteristic model, which is a Dynamic PLSPM in the statistical sense. This model can replace the dynamic product value-attribute model and provide more information to support the decision making at the front-end product concept screening phase. The newly introduced dynamic PLSR is fully utilized in formulating the dynamic path model, in order to make it a time variant structural relationship.

6.2 Dynamic Product Value-Characteristics Model Formulation

Based on the concepts and techniques introduced in Chapter 2, a dynamic product value-characteristic model is proposed with CRV as the indicator of overall product value. PLSR is proposed as the regression technique inside the PLSPM algorithm. This model can be used as the main decision support tool of the proposed framework for the strategic decision support. The overview of the dynamic product value-characteristics model formulation is given in the following subsection.

Overview

Dynamic product value-characteristics model formulation starts with a static model series formulation, similar to the dynamic product value-attribute modeling. The main inputs to the product value-characteristics models are the product attributes (formative type MVs) and

CRVs (reflective type MV), which is used as the sole product value indicator. The five phased overall methodology is given in the Figure 6-1.

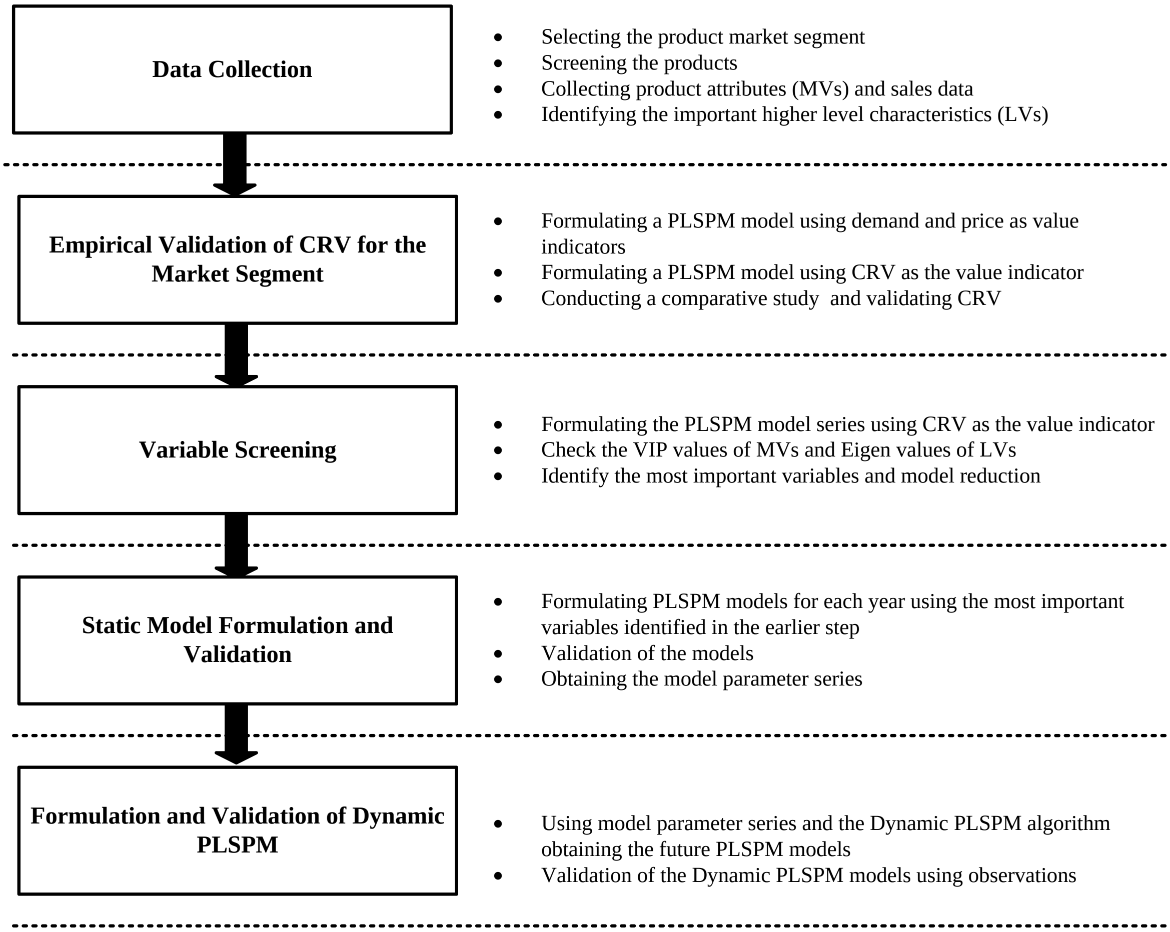

Figure 6-1 Overall Procedure of the Dynamic Product Value-Characteristics Modeling

A brief description of each phase that was conducted in order to obtain the proposed Dynamic PLSPM is provided in the following paragraphs.

First Phase: Market segment selection and data collection are the main tasks completed in this phase. Market segment selection is quite important in order to get an accurate set of CRV estimations. Prices, product sales, and product attribute levels can be used to correctly identify the market segments. Even inside a product market segment with similar product attribute levels, many partitions can be identified by carefully looking at price and demand. All available attribute data, prices, and sales data are collected from the initial time frame to the current time.

Second Phase: PLSPMs are formulated using all available attributes (formative MVs), prices, and sales (value indicators). LVs related to MVs are identified intuitively or by using market survey results or previous studies. This study attempts to cover all higher-level product characteristics, although data availability was limited throughout the time period. The next task is checking goodness of fit (GoF) of the overall product value LV. Correlations between CRV and overall product value LV are checked to confirm the validity of CRV as a value indicator for the market segment (Withanage et al. 2011).

Third Phase: After validating for the market segment, CRV is used as the sole value indicator, and GoF and model validation checks are completed. By identifying the most important attributes, model reduction is completed in this phase before starting the dynamic model formulation. Although there is not an exact method to select LVs for model formulation, the Eigen values of LVs can be used to get an idea of their significance. In practice, LVs with Eigen values larger than one are considered significant, which can be used as a standard when checking the significance of selected LVs (Wassenaar et al. 2004). The Variable Importance for Projection (VIP) (Eriksson et al. 2006) screening method, introduced in the previous research work (Withanage et al. 2010a) is used for the product attribute screening process. Only the product attributes with VIP>1 throughout the time period are selected to represent the market segment in this method. Finally, a simplified model is obtained for the dynamic model formulation.

Fourth Phase: The static model series from the initial time frame to the current time frame is formulated using the simplified model variables. Every model is validated using GoF and other measures.

Fifth Phase: Model parameter series are used to generate new parameter forecasts while preserving inherent structural properties (Wold et al. 2001; Eriksson et al. 2006). An optimization routine is used to find the optimal forecasting parameters, for the forecasting technique, by concurrently minimizing the forecasting and structural errors to gain a structurally sound future model. Various statistical time series forecasting techniques can be tested here, and the best technique can be selected to minimize the prediction error of CRVs.

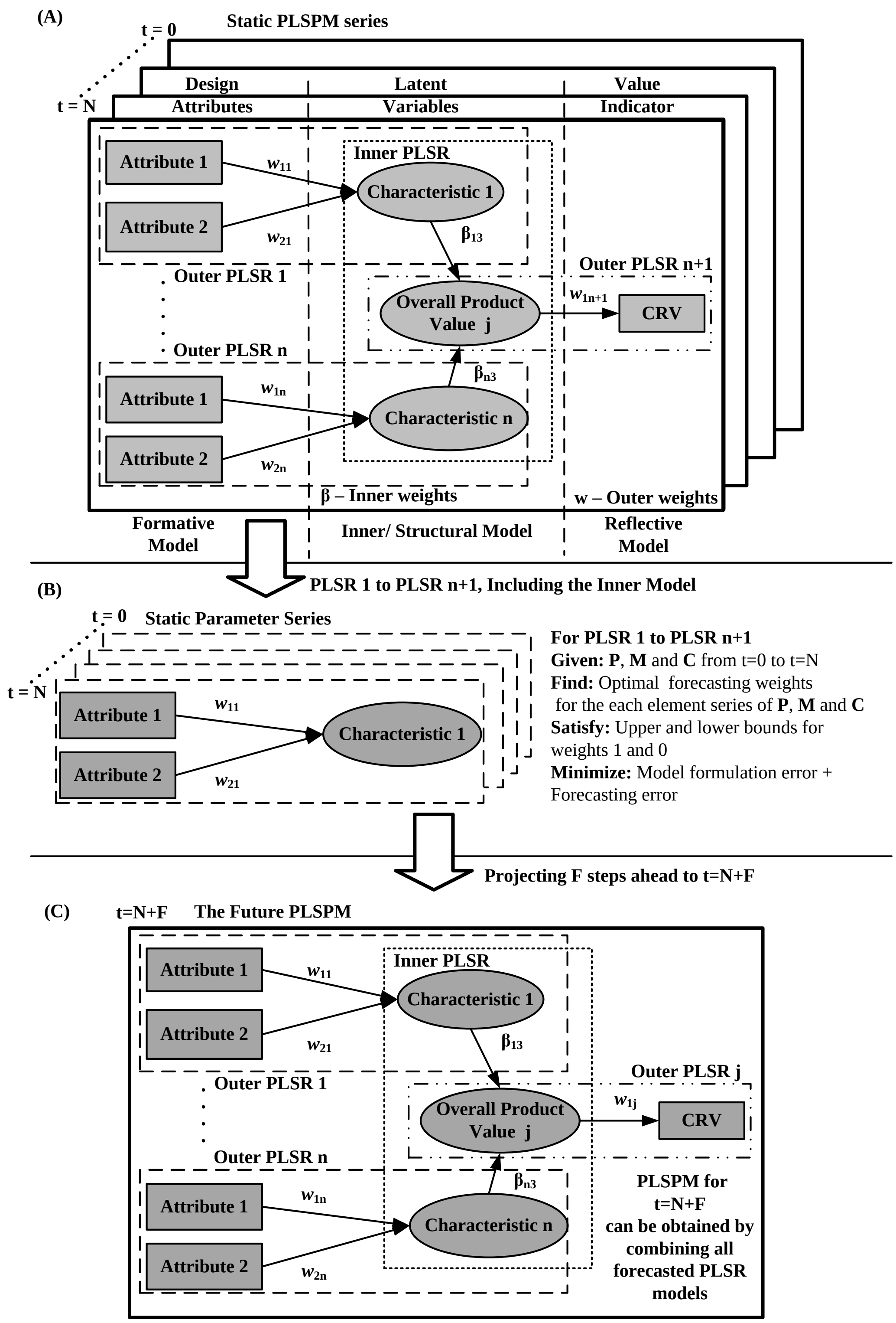

Figure 6-2 Overall procedure of the proposed Dynamic Partial Least Square Path Modeling (PLSPM) method

The overall procedure of the proposed Dynamic PLSPM method is given in Fig. 6-2. The parts (A), (B), and (C) represent the static PLSPM parameter series, the optimization problem formulation, and a projected future PLSPM, respectively. Different time series forecasting methods can be used in Part (B), and, finally, the future model parameters are projected using the PLSPM parameter time series.

The newly introduced framework may fit into any technological product market segment in order to get a dynamic product value-characteristic model using PLSPM. A background knowledge of product design cycle times and a general understanding of customer preferences in the market segment are prerequisites. More details about the model structure and algorithms are given in the following sections.

6.3 Case Study: Dynamic Partial Least Squares Path Modeling (PLSPM)

The procedure of the dynamic model formulation is depicted in Figure 6-2. The static PLSPM series is formulated first, using the model structure explained earlier. There are many PLSR models: one for each LV, plus one more for the structural model (see part (A) of Figure 6-2). These PLSR model parameters can be arranged as a time series to project the future models parameters. The earlier introduced Dynamic PLSR algorithm is used for this endeavour (Withanage et al. 2010a, Withanage et al. 2010b). Different time series forecasting techniques can be used to project future models. Finally, the projected set of future PLSR Models is combined to get the future path model.

The Dynamic PLSR algorithm is used to find optimal forecasting parameters in the proposed method. Minimization of forecasting errors and PLSR model formulation errors ensures a structurally sound future model at time period $t = N + F$ from the current time period $t = N$. Inside the Dynamic PLSPM algorithm (see Part (B) of Fig. 4), any time series forecast technique can be used to achieve optimal outputs.

Among the several methods within the exponential-smoothing family (Gardner 1985; Gardner 2006), the research scope was limited to additive and damped additive branches because of the limitations of multiplicative methods, which are incapable of handling the variations of the model parameters time series. In addition, the limited number of time series observations in the case study further narrows the scope to the set of smoothing methods without seasonal effects. The best forecasting technique can be selected by inspecting the behavior and the error aggregates of the forecasts, such as Mean Square Error (MSE) or Mean Absolute Percentage Error (MAPE) (Hyndman and Koehler 2006).

The structural integrity of the projected future models is ensured using PLSR model properties in the proposed approach. The orthonormal and orthogonal properties of the model parameters are combined to obtain a model formulation error term, which is used together with the forecasting errors. Hence, the optimal forecasting weights minimize the forecasting errors, and they also provide parameter forecasts with intact structural properties.

These forecasting weights are used to forecast future PLSR parameters using the parameter series of PLSRs, at t=1, 2, … N; finally, the future PLSPM of t=N+F is obtained by combining the future PLSR models (see Figure 6-2). The future PLSPM can be used to get the predictions of higher-level product characteristic values (LV scores) of new products, in addition to the overall product value or CRV estimations.

Market Segment Selection

The family sedan, a leading technological product from a well-established platform, was selected to show the applications of Dynamic PLSPM in the context of customer-driven design. Results of a survey, conducted by J. D. Power and Associates (Wassenaar et al. 2003; Wassenaar et al. 2005; Hoyle et al. 2010), further justify the market segment selection of this case study. According to the survey, customers in this market segment are more aware of technical specifications, and most choose cars based on levels of attributes.

Table 6-1 The number of selected car models for the yearly static model series

Year	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**
Car Models	34	32	34	34	40	41	38	39	35	41	35
Year	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**Total**
Car Models	36	36	32	27	25	26	26	28	27	24	**690**

A comprehensive case study was conducted using 21 years of annual car market data for US compact- and mid-sized sedans. Altogether, 690 market observations were included in the study. The number of observations for yearly static models varies between a minimum of 24 car models and maximum of 41 car models (see Table 6-1).

Data Collection, Screening of Variables, and Model Formulation

Sales, prices, and technical specifications, or design attribute values, were obtained from Ward's Automotive Group, and some were manually collected from 1990–2010. Brief descriptions of the five phases of the proposed Dynamic PLSPM method are given below.

First Phase: Car models were selected in this phase to accurately represent the family sedan market segment. The selection criteria were car size, price, and sales (Withanage et al. 2011), and 75% market segment representation was attempted to be maintained throughout the time period of 1990–2010. The lower tail of the yearly sales distribution and the upper tail of the yearly price distribution were ignored to determine the most popular low- to mid-level family sedan (see Figure 4-2), while still maintaining market representation.

Second Phase: In the proof of concept study with PLSPM, CRV was validated as a value metric for the family sedan market segment. Additionally, engine performance and comfort/convenience were identified as the most influential higher order characteristics, or LVs, similar to the study conducted by Hoyle et. al. (2010), and the J. D. Power survey outcomes mentioned in the paper. The results and observations of those studies were used for selecting the LVs and formulating the static PLSPM series in the next step.

Table 6-2 Higher level product characteristics and product attributes

Higher level characteristics	Product attributes	Comments
Engine Performance	Horsepower Torque Displacement MPG city MPG highway Bore Compression Stroke	The most significant LVs according to the pilot study (Withanage et al. 2011) and a customer survey (Wassenaar et al. 2005) Data continuing from 1990-2010
Comfort/ convenience	Wheelbase Front head room Rear head room Front shoulder room Rear shoulder room Front leg room Rear leg room Front hip room Real hip room Fuel tank volume	
Cost	MPG city MPG highway Resale index	Resale index data is not available for the whole time period and fuel efficiency is represented by the engine performance LV
Image	Brand rating Country of origin Length Height Width	Brand ratings are not available for the whole time period and this is not a highly significant LV according to the pilot study (Withanage et al. 2011)

Third Phase: A literature review was conducted to identify the most significant attributes and higher-level product characteristics, as mentioned earlier, for the overall product value in the sedan market segment (see Table 6-2). Leading car-rating systems, such as Consumer Reports, J. D. Power and Edmunds, were also examined to identify the attributes used in order to calculate the ratings.

Only the most significant LVs and MVs were selected to reduce the complexity of the optimization problem. According to previous case study results (Agarwal and Ratchford 1980; Arguea and Hsiao 1993; Arguea et al. 1994; Bhat et al. 2009, Berry et al. 1995; Donndelinger and Cook 1997; Hoyle et al. 2010; Petiot and Grognet 2006; Train and Winston 2007; Wassenaar et al. 2004) and market surveys, performance and comfort/convenience could be identified as the most important top-level customer desires, or the higher-level product characteristics, in this case study's market segment. Data availability and continuity (given in Table 6-2) were also considered before selecting the higher order characteristics for dynamic modeling.

XLSTAT software, equipped with PLSR for the parameter estimation (Temme et al. 2010), was used to get the static model parameter series. All available attributes to cover all aspects of engine performance and comfort/convenience were used to formulate the static model series (see Figure 6-3 for the initial and final sets of product attributes) from 1990–2008.

VIP values (Eriksson et al. 2006) were used to obtain a reduced model with the primary/most important attributes and secondary/second most-important attributes in the market segment. The attributes that were not at least VIP > 1, during one year, throughout the model series, were removed at the forefront. From the remaining set of attributes, only the attributes that are not represented by the existing attributes were added to the model to get a more representative model of the market segment.

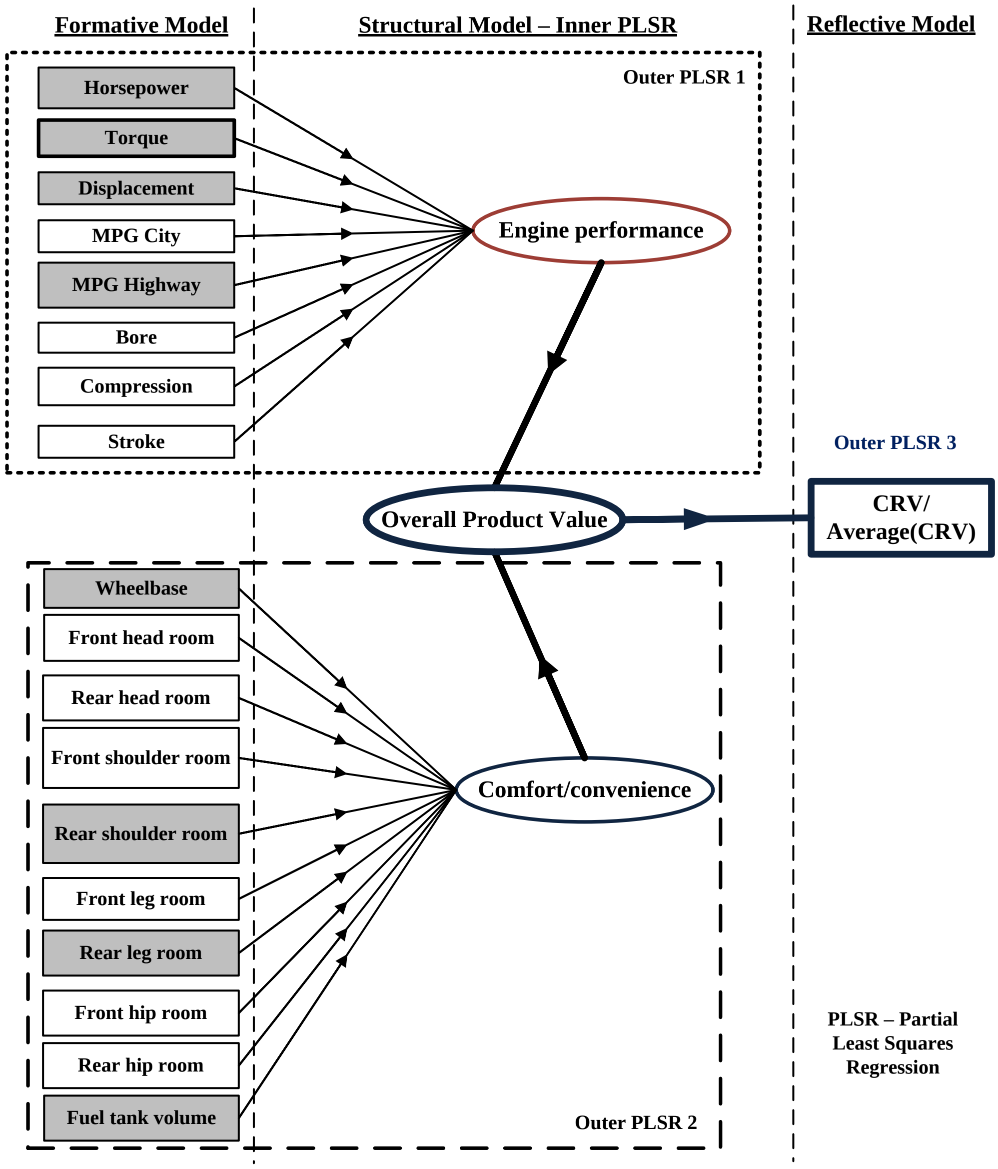

Figure 6-3 The Partial Least Squares Path Model (PLSPM) structure used for the initial static model formulation

In the engine performance module, horsepower, torque, and displacement were found to be the most significant variables when considering the VIP values over the time period. Highway fuel efficiency was added to the engine performance category to cover all dimensions in the original data set. The set of Engine Performance MVs, including displacement, horsepower, torque, and fuel efficiency, are highly correlated with each other according to their theoretical definitions (Erjavec 1996). Robust performances of

PLSR with multicollinear predictor variables enabled to make use of all the important variables and disregard their associations.

Inside the Comfort and Convenience block, wheelbase and fuel tank volume were the most significant MVs, closely followed by shoulder room. Finally, rear shoulder room and rear legroom were added to represent the dimensions significant to the family-car market segment. The selected attributes are indicated by the shaded boxes in Figure 6-3.

Fourth Phase. The static model series was formulated using performance and comfort as the higher-level characteristics, in addition to supporting attributes or manifest variables (formative type). The response variable was made more consistent over the years by using CRV of a car model divided by the average value of all CRVs of the market segment as the response variable.

The GoF of models and Eigen values of higher-level characteristics were inspected to ensure the validity of models. Model parameters series of Outer PLSR 1 (performance), Outer PLSR 2 (comfort), inner model, and Outer PLSR 3 (CRV) were collected. In the next phase, they were used as the time series observation for the dynamic model formulation.

Fifth Phase. The PLSPM models for 2009 and 2010 were projected through the market data from 1990–2008. The maximum length of observations was used in the parameter time series to get the concept-to-customer lead-time of future models. Since industrial concept-to-customer lead-time of a sedan is approximately 18 to 24 months (Monczka et al. 2009), one- and two-year ahead value forecasts were obtained.

The projected models were compared with the models formulated by observation for the validation of the model parameters. Mainly, CRV direct estimations were used for the Dynamic PLSPM CRV forecast validation. SES, DES and DA (Gardner 1985; Gardner 2006) were used as the forecasting techniques in the case study.

However, only the levels and trends of CRV were used for the dynamic model formulation, because the number of observations in the case study was not sufficient to capture the seasonal and cyclical time series properties (Garrett and Leatherman 2000). The direct search algorithm (Kolda et al. 2006) from MATLAB optimization toolbox was used to find the global optimal set of forecasting parameters. The strategy given in the following section was used to validate the proposed dynamic product value-characteristic modeling method.

Validation strategy

The data panels were divided to maximize the length of model parameter time series and to simulate the front-end design selection in the validation process. The data panels from 1990-2008 were used to formulate the static model series, and static models for the years 2009 and 2010 coupled with CRV observations were used for validation. The current concept-to-customer lead-time in the automobile industry is approximately one and a half years to two years (Monczka et al. 2009); hence, a two-year forecast was obtained in the model validation process to simulate the real industrial scenario in the case study.

Mean absolute percentage errors (MAPE) (Brockwell and Davis 2002; Hyndman and Koehler 2006) were used to assess the dynamic model predictions quantitatively. The CRV predictions of the Dynamic PLSPM and CRV observations were compared with each other to calculated the MAPE. The qualitative assessment of the projected future models were done by checking the trends of the real model coefficients, and how well the projected model coefficients track them, as well as the closeness of the coefficients.

The design decision makers are left with the latest static model (2008 in this case), if they are not using the proposed Dynamic PLSPM method. Then, they have to use the 2008 static model structure to understand the 2009 and 2010 product value-characteristics relationships. Thus, static model coefficients for 2008 and Dynamic PLSPM for 2009 and 2010 were compared in the case study with corresponding static models coefficients (2009 and 2010) to show the superiority of the Dynamic PLSPM method. Absolute percentage errors (APE) were calculated by using the model coefficients for 2008 and the real model coefficients for 2009 and 2010. They were compared with the APEs of the Dynamic PLSPM coefficient forecasts and real model coefficients, in order to depict the advantage of the dynamic/strategic over the static/traditional design approach.

Results

The results of the static model formulation, forecasting algorithm selection, projected future model structures, and CRV forecasts are given here. The static model series from 1990–2008 was used for the future model projection, and models of2009 and 2010 were kept for validation purposes.

The model quality assessment of static models is not straightforward due to the formative nature of the outer model. There are no standard metrics to assess formative models; however, GoF values obtained using observations and bootstrapping can be used for validation (Chin 2010a; Chin 2010b; Dijkstra 2010). Overall and bootstrapped GoFs are falling within healthy regions around 0.90 (see Table 6-3). Furthermore, it can be seen that outer model GoF is sacrificed for the inner model, which is the typical scenario in a formative type of an outer model (Chin et al. 2010a; Chin et al. 2010b). Forecasting technique selection was carried out after model validation, and forecasting errors were calculated using real observations to select the best technique for the data set.

SES, DES and DA from the exponential-smoothing family, were used to select the best technique for the data set. Two sets of CRV forecasts for 2009 and 2010 were obtained and MAPEs were calculated and compared to select the best technique. As a result, in this case study, the DA forecasting technique was selected for dynamic model formulation to minimize the MAPE of CRV predictions (see Table 6-4).Dynamic PLSPM LV forecasts and CRV forecasts are given in Table 6-5 for the years 2009 and 2010. The CRV forecasts were compared with the CRV observations to calculate APEs, and, finally, MAPEs were obtained for the years 2009 and 2010.

Table 6-3 Goodness of fit (GoF) and goodness of fit bootstrap (B.S.) values of static models

	1990		1991		1992		1993		1994		1995		1996	
	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.
Absolute	0.59	0.60	0.66	0.68	0.72	0.70	0.66	0.64	0.61	0.62	0.71	0.71	0.73	0.70
Relative	0.84	0.80	0.87	0.85	0.90	0.85	0.85	0.80	0.84	0.79	0.92	0.88	0.89	0.84
Outer model	0.86	0.83	0.89	0.88	0.91	0.87	0.91	0.86	0.85	0.82	0.95	0.92	0.91	0.86
Inner model	0.97	0.96	0.97	0.97	1.00	0.98	0.93	0.92	0.98	0.96	0.97	0.96	0.98	0.98

	1997		1998		1999		2000		2001		2002		2003	
	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.
Absolute	0.71	0.70	0.75	0.74	0.72	0.72	0.68	0.67	0.80	0.73	0.77	0.76	0.65	0.64
Relative	0.92	0.88	0.90	0.84	0.91	0.88	0.84	0.81	0.91	0.83	0.92	0.89	0.80	0.76
Outer model	0.94	0.91	0.95	0.90	0.94	0.91	0.87	0.84	0.92	0.85	0.94	0.92	0.82	0.80
Inner model	0.98	0.97	0.94	0.94	0.97	0.97	0.96	0.96	0.98	0.98	0.98	0.97	0.97	0.95

	2004		2005		2006		2007		2008		2009		2010	
	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.	GoF	GoF B.S.
Absolute	0.80	0.77	0.71	0.68	0.74	0.74	0.72	0.71	0.75	0.74	0.86	0.83	0.81	0.79
Relative	0.91	0.87	0.89	0.81	0.90	0.85	0.94	0.87	0.89	0.84	0.95	0.91	0.94	0.89
Outer model	0.93	0.90	0.93	0.87	0.93	0.89	0.96	0.91	0.92	0.88	0.96	0.92	0.95	0.91
Inner model	0.98	0.97	0.96	0.94	0.97	0.96	0.99	0.95	0.96	0.96	0.99	0.99	0.98	0.97

Generally, forecasts with MAPE<10 are considered highly accurate (Lewis 1982) and the final MAPE of 3.40 shows the potential of the proposed method as a design decision support tool.

The forecast and observed CRVs were compared to see if there was any significance using a paired t-test for 2009 and 2010. The results of the t-tests (degree of freedom =27, t-score = -0.40, *p-value = 0.694*; and degree of freedom = 24, t-score = 0.20, *p-value = 0.844*), with high p-values, indicated the the difference between forecasts and observations is not significant.

Table 6-4 Forecasting Technique Selection

Forecasting technique	MAPE	
	2009	**2010**
SES	1.8764	3.4087
DES	1.8782	3.3931
DA	1.8604	3.3846

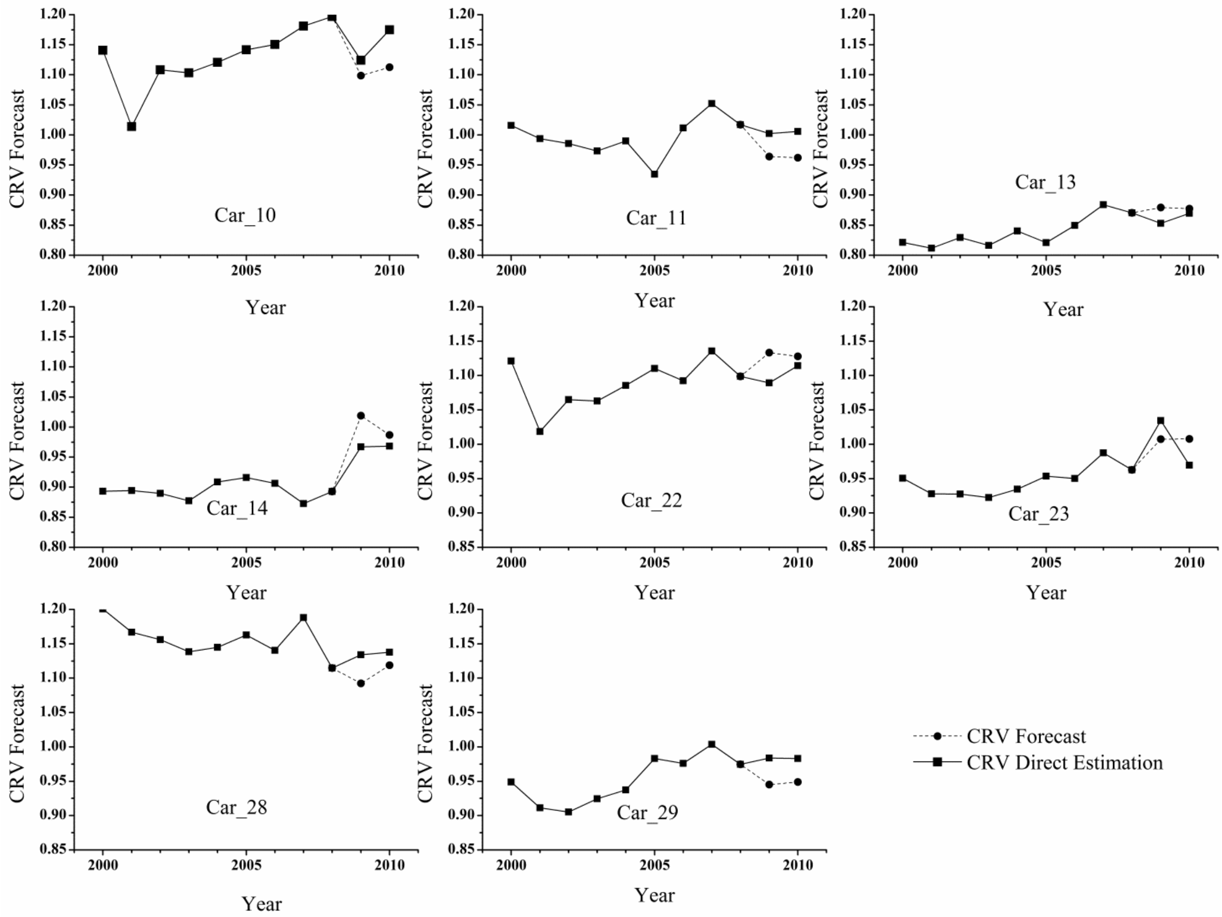

Figure 6-4 Customer Revealed Value (CRV) time series of selected car models

Table 6-5 Latent Variable (LV) and Customer Revealed Value (CRV) forecasts

	2009					2010				
Car Model	**Perf.**	**Com./ Con.**	**CRV for.**	**CRV obs.**	**APE**	**Perf.**	**Com./ Con.**	**CRV for.**	**CRV obs.**	**APE**
Car_1	-1.65	-1.45	0.86	0.88	1.47	-1.55	-1.40	0.87	0.82	5.57
Car_2	0.39	-0.73	0.97	0.97	0.26	0.33	-0.78	0.97	0.91	6.24
Car_3	0.74	0.76	1.07	1.08	1.14	0.57	0.83	1.06	1.13	6.03
Car_4	0.87	1.01	1.09	1.08	0.99					
Car_5						0.74	0.98	1.08	1.04	3.77
Car_6						0.74	1.02	1.08	1.05	3.41
Car_7						-0.54	-0.44	0.96	0.98	2.68
Car_8	-0.07	-0.58	0.96	0.94	2.28	-0.14	-0.53	0.97	0.97	0.67
Car_9	0.32	0.93	1.06	1.08	1.48	1.09	0.97	1.09	1.09	0.22
Car_10	0.95	1.19	1.10	1.11	0.98	1.05	1.41	1.11	1.17	5.29
Car_11	-0.51	-0.34	0.96	0.93	3.44	-0.56	-0.35	0.96	1.01	4.36
Car_12	-1.62	-1.76	0.85	0.85	0.28	-1.67	-1.74	0.85	0.90	6.05
Car_13	-1.50	-1.26	0.88	0.86	1.92	-1.59	-1.26	0.88	0.87	0.86
Car_14	-0.34	0.52	1.02	1.00	2.23	-0.29	-0.06	0.99	0.97	1.91
Car_15	1.09	1.00	1.09	1.10	0.93	1.00	1.05	1.09	1.11	2.13
Car_16	1.11	0.61	1.07	1.10	2.25					
Car_17	-1.72	-1.26	0.87	0.86	1.15					
Car_18	-0.57	-0.40	0.96	0.97	1.66					
Car_19						0.15	-0.17	1.00	0.93	7.24
Car_20	0.16	-0.25	0.99	1.04	4.50	-0.21	-0.20	0.98	0.99	0.97
Car_21	0.89	1.30	1.10	1.14	3.58	0.74	1.36	1.10	1.06	3.57
Car_22	1.31	1.59	1.13	1.14	0.29	1.31	1.53	1.13	1.11	1.24
Car_23	-0.13	0.20	1.01	1.01	0.50	-0.07	0.19	1.01	0.97	3.93
Car_24	-1.09	-1.21	0.90	0.88	1.61	-1.16	-1.09	0.90	0.86	4.48
Car_25	0.59	0.94	1.07	1.08	0.45					
Car_26	0.74	0.26	1.04	1.01	3.09					
Car_27	0.74	0.49	1.05	1.01	4.20					
Car_28	0.60	1.27	1.09	1.11	1.78	1.34	1.35	1.12	1.14	1.64
Car_29	-0.67	-0.58	0.95	0.93	1.26	-0.68	-0.51	0.95	0.98	3.48
Car_30	-1.64	-1.69	0.85	0.83	1.97	-1.59	-1.64	0.86	0.85	0.22
Car_31	1.01	-0.53	1.00	1.05	4.51	0.98	-0.53	1.00	1.06	5.28
			MAPE		**1.86**					**3.38**

The car models from 2000–2010 were selected to represent the CRV time series given in Figure 6-4. The CRV given in the y-axis represents the perceived value of a car model generated by its levels of attributes. The solid line represents the market observations, and the dotted line represents the dynamic model predictions.

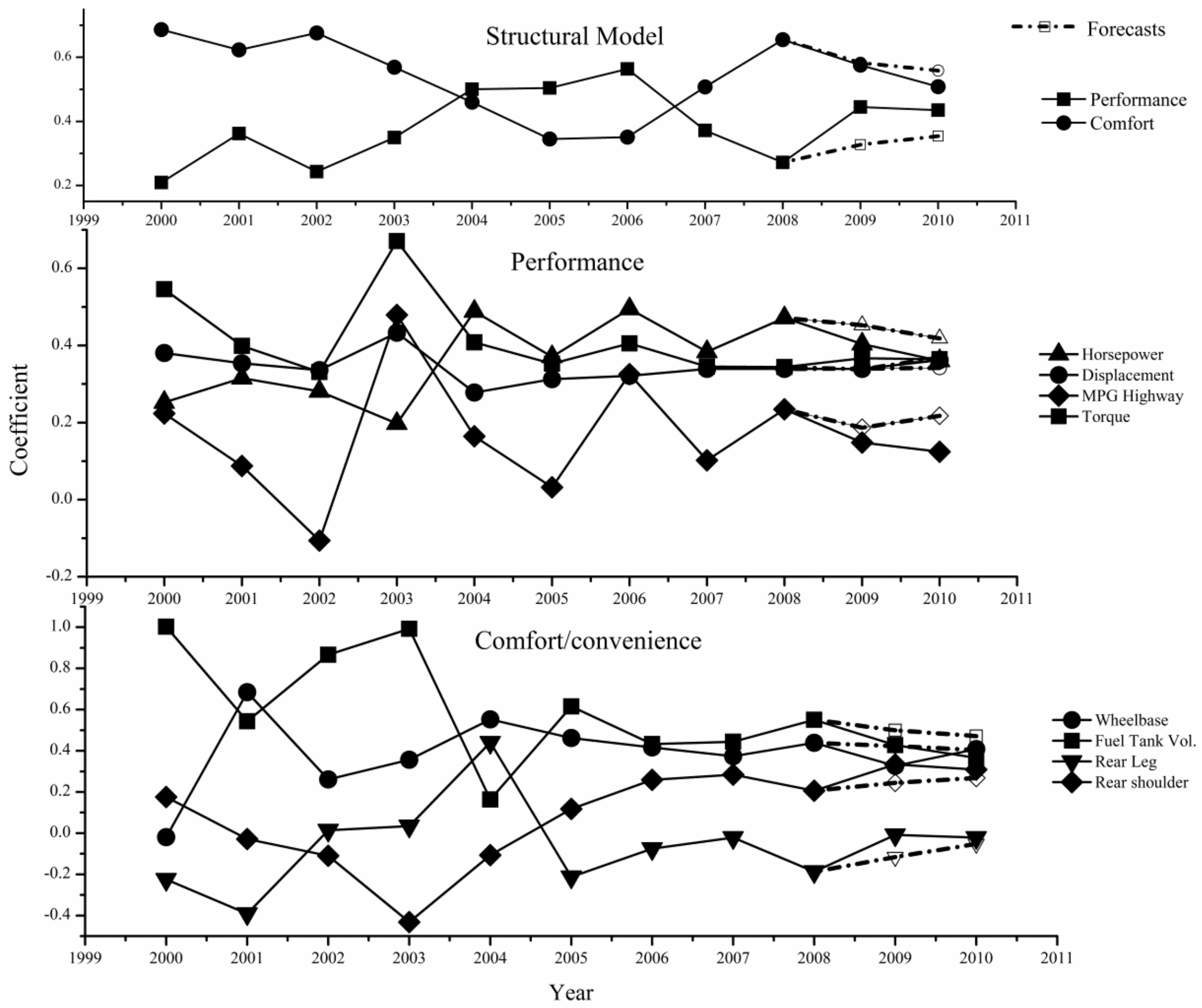

Figure 6-5 Coefficient time series and forecasts from year 2008

The performance of the Dynamic PLSPM was quantitatively evaluated using the real model coefficients, in addition to the qualitative assessment depicted in Figure 6-5. The APE comparison given in Table 6-6 and the CRV time series clearly show the evidence of inept performance for static coefficients of 2008, as substitutes for the future coefficients for 2009 and 2010. This result supports the advantages of dynamic product value-characteristic modeling over static modeling for this market segment.

Table 6-6 Model parameter forecasts and observations

	2008	2009				2010			
		Coefficients/Loadings		APE		Coefficients/Loadings		APE	
Variable	Observ. (Latest Static)	Observ. (Real)	Forecast (Dynamic)	Real vs. Dynamic	Real vs. Static	Observ. (Real)	Forecast (Dynamic)	Real vs. Dynamic	Real vs. Static
Displ.	0.3392	0.3393	0.3418	0.0074	0.0003	0.3621	0.3418	0.0561	0.0632
HP	0.4717	0.4040	0.4183	0.0354	0.1676	0.3603	0.4183	0.1610	0.3092
HW. F.E.	0.2345	0.1484	0.2178	0.4677	0.5802	0.1244	0.2178	0.7508	0.8850
TQ	0.3441	0.3667	0.3688	0.0057	0.0616	0.3642	0.3688	0.0126	0.0552
Wheelb.	0.4390	0.3270	0.4039	0.2352	0.3425	0.4079	0.4039	0.0098	0.0762
Fuel cap.	0.5504	0.4274	0.4710	0.1020	0.2878	0.3655	0.4710	0.2886	0.5059
Rear leg	-0.1872	-0.0086	-0.0524	5.0930	20.7674	-0.0218	-0.0524	1.4037	7.5872
Rear should	0.2063	0.3340	0.2683	0.1967	0.3823	0.3083	0.2683	0.1297	0.3308
Perform.	0.2716	0.444	0.3274	0.2626	0.3883	0.435	0.3540	0.1862	0.3756
Comfort/ Conven.	0.6550	0.575	0.5836	0.0150	0.1391	0.508	0.5582	0.0988	0.2894

Discussion

A front-end product concept screening scenario in an automobile-manufacturing firm was simulated in the case study. The car models for 2009 and 2010 can be considered product concepts wanted to be evaluated for 2008. In this scenario, the most important output is pure characteristic value, with disregard to marketing effects, since we are selecting from products with the same level of brand power, reputation, and so on. Additionally, the product value-characteristic relationship, free of characteristics-price trade-off, makes this method unique.

The two main outputs of Dynamic PLSPM, the new product CRV forecasts and the future product value-characteristic model parameters, were used to assess the model performances quantitatively and qualitatively. It can be seen that Dynamic PLSPM is providing accurate forecasts with MAPE<3.40, using few variable inputs.

The time series in Figure 6-4 depicts the time varying preferences and inadequacy of the static product value-characteristic modeling approach for the concept evaluation in technological product development. The coefficient time series (see Figure 6-5) provide strong evidence and support the decision to use the proposed dynamic methods, where the latest available static coefficients for 2008 are far from the real model coefficients for 2009 and 2010. The forecasts clearly follow the real coefficients' variations closely.

Interesting trends can be seen in the coefficient time series. From the distant state in 2008, inner model path coefficients of performance and comfort/convenience were getting closer by 2010. In addition, all three primary performance variables are becoming closer to each other in terms of influence on performance LV. Fuel efficient and powerful cars are generating more value, according to the analysis of the family sedan market segment. The value, or the level of importance, for these performance attributes is slowly increasing in comparison to comfort and convenience variables, and this reflects the current market dynamics.

The reason behind the increasing interest of engine specifications and power can be attributed to customers moving from the SUV/Pickup and other market segments (Baum 2011). The recent engine upgrades of popular Asian cars (see Consumer Reports and other auto review websites), and the increasing popularity of other powerful but fuel-efficient cars, can be considered real-world evidence of our case study results.

There are few high errors generating cars (see Figure 6-4 and Table 6-5), and those can be attributed to random errors, plus the effect of brand image and other factors ignored in the Dynamic PLSPM formulation process. The marketing effects such as promotions, reliability issues and similar factors can influence the price and demand of car models in the selected market segment. These factors were not captured by the formulated dynamic product value-characteristic model, but they can influence the CRV observations. Therefore, high errors can be observed in some cases, due to this limitation in variable selection. For example, the global recession was occurred in 2007-2008, and 2009 was inside the recovery phase. Hence, some inaccuracies could be caused by the irregular customer and market behavior (random components) during this time period.

Also, forecasting algorithms and the process itself can contribute to the errors found in the results. A time series has systematic (i.e., level, trend, seasonality) and random components. Unfortunately, a typical time series forecasting method only captures the systematic components (Chopra and Meindl 2001). Only levels and trends were captured in the Case Study, while the seasonality was not captured due to the limitations in data availability. Therefore, random and seasonality components could be the reasons behind the deviations of forecasts.

The set of results given in Table 6-3 shows an interesting trend. Clearly, it can be seen that the introduction of more time-varying properties in to the model provides more accurate results. Due to the limited time series observations (length of the time series), the damped additive method was selected without trying seasonal exponential techniques. If there are more time series observations available (more yearly panels of data), forecasting techniques such as ARIMA, ARMA, in addition to seasonal ones, can be tested before selecting the best technique for the data set. Furthermore, the model structure and variables can be changed to suite the market segment considered in the analysis.

The benefits of using PLSR can be shown using the observations sets. All MV observation sets have received high condition numbers (Mason and Perreault 1991), exceeding 10, in most of the years and reaching 50 in others. The condition number of a data set can be calculated by taking the ratio between highest and lowest Eigen values; the high condition numbers are indicators of multicollinearity among design variables. In addition, the correlation matrices of manifest variable blocks provide strong evidence of multicollinearity among manifest variables.

In particular, MVs connected to Engine Performance LV are highly correlated with each other, with correlation coefficients around 0.90 throughout the time period considered in the analysis.

This method can be used in any segment of the technology market by replacing the latent variables and the set of attributes with the significant variables for the market segment considered. Knowledge of consumer behaviour in the market segment is a prerequisite for the higher level and attributes level variable selection processes. The same procedure can be used step-by-step to formulate a Dynamic PLSPM considering the concept-to-customer cycle time in the industry, in order to support front-end decision making in the context of customer-driven design.

6.4 Closure

A dynamic product value-characteristics model was proposed and validated to support front-end product concept screening process in this chapter. The proposed dynamic model is intended to address the third Research Question (*RQ3*). Dynamic PLSR, the main contribution given in Chapter 5, was used to formulate this extended value model with higher level characteristics. This model can be used to evaluate the product concepts in two levels, using the top level overall product values and using intermediate system level characteristic values, to support the front-end PDD decision making. Also, Dynamic PLSPM is a novel method, which is introduced to address the lack of dynamic preference modeling methods in PDD. The proposed Dynamic PLSPM method can be used as the decision support tool of the Strategic Decision Support Framework

Previously validated techniques and components are used in the proposed method to ensure the theoretical structural validity (Pedersen et al. 2000). The satisfactory results obtained in the US sedan market case study can be used for the empirical performance validation of the proposed method. Furthermore, this research can be extended with the availability of more data by quantifying the data uncertainty (Choi and Allen 2009). The main contributions, limitations and the future works of the overall research study, presented in the thesis, are given in Chapter 7.

7 CONCLUSIONS

7.1 The Main Theoretical and Practical Contributions

The research study presented in this thesis is proposed to address three research gaps presents in the current design theory and methodology research. Mainly, this research study is proposed to reduce the model uncertainty coming in many faces during product value modeling.

The existing modeling methods suffer from the multicollinearity, endogeneity and higher dimensional data, where the number of observations is limited by nature. Especially, revealed value analysis, where customer attributes are not available all the time, makes the number of independent observations limited to number of products in the market segment. In addition to all these problems related with the design data and availability of data, the volatile nature of technological markets and the dynamic preferences pose whole new set of challenges.

Currently used modeling methods are inadequate to handle these challenges. Hence, a robust product value-attribute model, a dynamic product value-attribute model and a dynamic product value-characteristics model were proposed as the solutions to those shortcomings. The multivariate analysis methods, PLSR and PLSPM, were used to overcome the shortcomings of the design data. Novel Dynamic PLSR and PLSPM methods were introduced as the solution to handle the dynamic nature of the market. Ultimately, a Strategic Decision Support Framework was formulated to incorporate the market dynamics in the front-end product concept screening process, using the proposed dynamic modeling methods as decision support tools.

There are four key contributions of the thesis, as pointed out in Figure 3-2. The contributions and brief descriptions of them are given below.

1. The product value-attribute meta-model: A theoretical foundation is provided for the multivariate analysis models of the product value-attribute relationship. This is derived using the value curves and utility functions (Donndelinger & Cook 1997). This theoretical relationship defines the coefficients of the regression models, which are used for the product value-attribute relationship estimation in RVMs.

2. Robust Partial Least Squares Regression (PLSR): A Robust PLSR algorithm is introduced to minimize the effect of heteroscedasticity. The weighted least square approach (Choi et al. 2009) and variance parameter estimation (Davidian and Carroll 1986) approaches are followed to formulate this novel algorithm. This can be used with the data sets plagued with heteroscedasticity to estimate robust models.

3. Dynamic Partial Least Squares Regression (PLSR): A Dynamic PLSR algorithm is formulated as the third contribution of this research study. This method is developed to address the model uncertainty in the current preference analysis by introducing dynamic models. Mainly, this can be used for the front-end concept screening, considering the effects of the concept-to-market lead time on customer preferences. Furthermore, this novel algorithm can be used to formulate dynamic models beyond the provided product value-attribute modeling applications.

4. Dynamic Partial Least Squares Path Modeling (PLSPM): A Dynamic PLSPM algorithm is introduced in this thesis. This can be considered as an extension of the dynamic product value-attribute modeling method by including higher level product characteristics or Latent Variables (LVs). In addition to the benefits of the dynamic modeling mentioned before, this method facilitates the decision makers with two levels of decision variables, the overall product value and higher level characteristic values. The higher level product characteristics are closer to the customers and they cannot be measured directly. Hence, this method provides a unique opportunity for the design decision makers to evaluate concepts in different levels.

In addition to these key contributions, a few more noteworthy research outcomes can be found in the thesis. PLSR and PLSPM, popular methods from chemometrics and social sciences, were introduced to the PDD research community through various publications in different stages of the research study. The strengths of these multivariate analysis methods were introduced, and the benefits were shown through the case studies conducted using real market data (Withanage et al. 2010a; Withanage et al. 2010b; Withanage et al. 2011; Withanage et al. 2012).

Furthermore, using the LV modeling method, the CRV analyses were extended for the first time (Withanage et al. 2011) to include the higher level product characteristics. Also, the empirical validation of the proposed "pure characteristic value modeling" approach and usefulness of CRV as a value indicator (Withanage et al. 2011) were conducted using the PLSPM. The results of the case studies reflected the potential of the proposed framework, as an industrial design decision support tool.

The proposed Strategic Decision Support Framework can be used to assess the technological product concepts with quantifiable attributes, in the front-end product concept screening process. Especially, products with longer concept-to-customer lead times are the best candidates for the application of the proposed framework. In addition to cars used in the case studies, other automobile product market segments such as pick-up trucks, CUVs (Crossover Utility Vehicles), SUVs (Sports Utility Vehicles) and mini vans can be evaluated using the proposed framework. Also, the framework can be used in other well established technological product market segments such as flat-panel televisions and laptop computers to select the best product concepts, in the context of customer driven design.

7.2 Limitations and Future Works

The research study presented in this thesis is started with a narrowed down scope, targeting the technological product market segments. In addition, products with longer concept-to-design cycle times were identified as the most benefitted technological products by the proposed decision support framework. Furthermore, some fundamental, methodological and practical limitations can be identified in the proposed approach.

Fundamentally, the proposed approach is based on the rational behaviour of the customers, which is subjected to still ongoing debates in economic research circles. This is a matter of concern, though the stability of whole economy is based on rational behaviour. Thus, sensible, planned and consistent customer behaviour can be viewed as a regular practice (McFadden 1999).

Methodologically, there are few more limitations. The selected value metric, CRV is an estimated value from a micro economic analysis. Hence, errors can be introduced to the estimated models through the CRV estimations. Furthermore, the proposed method was limited to the Revealed Preference type data. The Stated Preference type data was not considered in the proposed framework. In addition, the random components of the model parameter time series can always cause deviations from the real values.

Practically, the availability of data is the most influential limitation, which did not permit the generalization of the study beyond the Sedan market segment. The most difficult task was collecting attribute data continuously for twenty years. But, the attribute data is available for the product designers through their corporate databases; hence, this will not marginalize the usefulness of the proposed framework as an industrial decision support method.

Due to the limitations of data availability, exponential smoothing methods are used as the only time series techniques in the presented case studies. The exponential methods with seasonality or the other advanced time series forecasting techniques can be used with the availability of more time series data. Levels and trends are the only captured time series properties in the presented case studies, and the seasonal forecasting methods may improve the accuracy of model parameter forecasts.

Generalization of the proposed framework using real data from different technological product market segments is the immediate future work proposed for this research study. Also, extending the Robust PLSR method to dynamic modeling is proposed as the second future work.

This will be a challenging work due to the added complexity, increased mathematical burden, and loss of degree of freedom.

The proposed framework can be improved by using a new value metric to overcome the linear demand assumption of CRV. However, CRV is an end result of a research spanned more than a decade, and inventing a new value metric will be an uphill task. Also, advance time series forecasting techniques can be used to get more accurate model parameter forecasts with the availability of more time series observations (data panels). A value metric with a better representation of perceived value and the use of advance time series forecasting techniques with more accurate model parameter forecasts will make the proposed framework more appealing to the industry. In addition, with the availability of more data, other types of modeling uncertainties can be assessed in the dynamic value-attribute and value-characteristic modeling.

Although, there are some limitations as mentioned here, the strengths of the proposed framework can be used within the given boundaries to get accurate results, as shown in the case studies. The proposed framework is a forerunner of the dynamic product value models and dynamic design decision support methods in the PDD literature.

Bibliography

Agarwal, M. K., & Ratchford, B. T. (1980). Estimating demand functions for product characteristics: the case of automobiles. *Journal of Consumer Research*, 7(3), 249-262.

Akay, D., & Atak, M. (2007). Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. *Energy, 32*(9), 1670-1675.

Akao, Y. (1994). Development history of quality function deployment. In S. Mizuno & Y. Akao (Eds.), *QFD: The Customer Driven Approach to Quality Planning and Deployment* (pp. 339-351). Tokyo, Japan: Asian Productivity Organization.

Amann, K. (2002). *Product lifecycle management: Empowering the future of business*, Ann Arbor, MI: CIM Data.

Antonsson, E. K., & Otto, K. N. (1995). Imprecision In Engineering Design. *Journal of Mechanical Design, 117*, 25-32.

Arguea, N. M., & Hsiao, C. (1993). Econometric issues of estimating hedonic price functions: With an application to the U.S. market for automobiles. *Journal of Econometrics, 56*(1/2), 243-267.

Arguea, N. M., Hsiao, C., & Taylor, G. A. (1994). Estimating consumer preferences using market data: An application to us automobile demand. *Journal of Applied Econometrics, 9*(1), 1-18.

Arrow, K. J. (1950). A Difficulty in the Concept of Social Welfare. *Journal of Political Economy,* 58, 328-346.

Baum, A. (2011). Fuel Costs Move the Market. *A Look at U.S. Automative Sales Trends*. Retrieved from http:// www.baum-assoc.com/Documents.

Belloni, A. , Freund, R., Selove, M., & Simester, D. (2008). Optimizing product line designs: Efficient methods and comparisons. *Management Sci*ence*, 54*(9), 1544-1552.

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D., Morikawa, T., & Polydoropoulou, A. (2002). Integration of choice and latent variable models. In H.S. Mahmassani (Ed.), *Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges* (pp. 431-470). Oxord, UK: Elsevier.

Bergquist, K., & Abeysekera, J. (1996). Quality function deployment (QFD): a means for developing usable products. *International Journal of Industrial Ergonomics, 18*(4), 269–275.

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica, 63*(4), 841-890.

Bhat, C. R., Sen, S., & Eluru, N. (2009). The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. *Transportation Research: Part B, 43*(1), 1-18.

Bisgaard, S., & Kulahci, M. (2011). Additional Issues in ARIMA Models *Time Series Analysis and Forecasting by Example*. Hoboken, NJ: John Wiley & Sons, Inc.

Blau, J. H. (1957). The Existence of Social Welfare Functions. *Econometrica, 25*, 302-313.

Boothroyd, G., Dewhurst, P. & Knight. W.A. (1994). *Product Design for Manufacturing and Assembly*. New York, NY:M. Dekker.

Box, G. E. P., & Meyer, R. D. (1986). Dispersion effects from fractional designs. *Technometrics, 28*(1), 19-27.

Box, G. E. P., & Jenkins, G. M. (1970). *Time series analysis: Forecasting and control*. San Francisco, CA: Holden Day.

Brockwell, P. J., & Davis, R. A. (2002). *Introduction to Time Series and Forecasting.* New York, NY:Springer-Verlag.

Brown, R. G. (1959). *Statistical forecasting for inventory control*. New York, NY: McGraw-Hill.

Brown, S.L., & Eisenhardt, K.M. (1995). Product development: Past research, present findings, and future directions. *Academy of Management Review, 20*, 343–378.

Burns, D. A. & Ciurczak, E. W. (2007). *Handbook of Near-infrared Analysis*. New York, NY: CRC Press.

Calantone, R. J., Di Benedetto, C. A., & Schmidt, J. B. (1999). Using the analytic hierarchy process in new product screening. *Journal of Product Innovation Management, 16*(1), 65-76.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. New York, NY: Cambridge University Press.

Capon, N. & Palij, P. (1994). Strategic marketing forecasting, market segment selection and firm performance. *International Journal of Forecasting, 10*(2), 339-352.

Carrascal, L. M., Galván, I., & Gordo, O. (2009). Partial least squares regression as an alternative to current regression methods used in ecology. *Oikos, 118*(5), 681-690.

Carroll, J.D., & Green, P.E. (1995). Psychometric methods in marketing research: Part I, conjoint analysis. *Journal of Marketing Research, 32*(4), 385-391.

Chin, W. W. (1995). Partial Least Squares is to LISREL as principal components analysis is to common factor analysis. *Technology Studies, 2*, 315-319.

Chin, W. W. (2010a). Bootstrap cross-validation indices for pls path model assessment. In V. E. Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 83-97), Berlin, Germany: Springer-Verlag.

Chin, W. W. (2010b). How to write up and report pls analyses. In V. E. Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 655-690), Berlin, Germany: Springer-Verlag.

Choi, H. J., & Allen, J. K. (2009). A metamodeling approach for uncertainty analysis of nondeterministic systems. *Journal of Mechanical Design, 131*(4), 041008-041010.

Choi, H. J., Austin, R., Allen, J. K., McDowell, D. L., Mistree, F., & Benson, D. J. (2005). An approach for robust design of reactive power metal mixtures based on non-deterministic micro-scale shock simulation. *Journal of Computer-Aided Materials Design, 12*(1), 57-85.

Chopra, S., & Meindl, P. (2001). *Supply Chain Management: Strategy, Planning and Operation*. New Jersey, NJ: Prentice Hall.

Churchman, C. W. & Ackoff, R.L. (1954). An approximate measure of value. *Operation Research, 2*, 172-187.

Cook, H. E. (2006). The role of demand modeling in product planning. In K. E. Lewis, W. Chen, & L. C. Schmidt (Eds.), *Decision Making in Engineering Design* (pp. 109-122), New York, NY: ASME.

Cook, H. E., & Gill, M. R. (1992). On system design. *Research in Engineering Design, 4*(4), 215-226.

Cook, H. E., & Kolli, R. P. (1994). Using value benchmarking to plan and price new products and processes. *Manufacturing Review, 7*(2), 134 -147.

Cook,H.E, & Wissmann, L.A. (2007). Value Driven Product Planning and Systems Engineering, London, UK: Springer-Verlag.

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA)–Thirty years on. *European Journal of Operational Research*, *192*(1), 1-17.

Cudney, E. A., Paryani, K., & Ragsdell, K. M. (2006). Applying the Mahalanobis-Taguchi system to vehicle handling. *Concurrent Engineering-Research and Applications, 14*(4), 343-354.

Dangerfield, B. J. & Morris, J. S. (1992). Top-down or bottom-up: Aggregate versus disaggregate extrapolations. *International Journal of Forecasting, 8*(2), 233-241.

Davidian, M., & Carroll, R. J. (1987). Variance function estimation. *Journal of the American Statistical Association, 82*(400), 1079-1091.

De Gooijer, J. G. & Hyndman, R. J. (2006). 25 years of time series forecasting. *International Journal of Forecasting, 22*(3), 443-473.

De Lurgio, S. A. (1998). *Forecasting Principles and Applications*, New York, NY: McGraw Hill.

Dijkstra, T. K. (2010). Latent variables and indices: Herman Wold's basic design and partial least squares. In V. E. Vinzi, W. W. Chin, J. Henseler & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 23-46). Berlin, Germany: Springer-Verlag.

Donndelinger, J. & Cook, H. E. (1997). Methods for analyzing the value of vehicles. *Journal of Passenger Cars, 106*, 1263-1281.

Downen, T. D., Nightingale, D. J., & Magee, C. L. (2005). Multi-attribute value approach to business airplane product assessment. *Journal of Aircraft, 42*(6), 1387- 1395.

Eriksson, L., Joahansson, E., Kettaneh-Wold, N., Trygg, J., Wikstrom, C., & Wold, S. (2006). *Multi and Megavariate Data Analysis Part 1*. Umea, Sweden: Umetrics Academy.

Erjavec, J. (1996). *Automotive Technology: A Systems Approach*, Clifton Park, NY: Thomson Delmar Learning.

Fernández, M. G., Seepersad, C. C., Rosen, D. W., Allen, J. K., & Mistree, F. (2005). Decision support in concurrent engineering: The utility-based selection decision support problem. *Concurrent Engineering, 13*(1), 13-27.

Finger, S., & Dixon, J.R. (1989a). A review of research in mechanical engineering design, part I: Descriptive, prescriptive, and computer-based models of design processes. *Research in Engineering Design, 1*(1), 51–68.

Finger, S., & Dixon, J.R. (1989b). A review of research in mechanical engineering design, part II: Representations, analysis, and design for the life cycle. *Research in Engineering Design, 1*(2), 121–137.

Fishburn, P.C. (1968). Utility theory. *Management Science, 14*(5), 335-378.

Fishburn, P.C. (1970). Arrow's impossibility theorem: Concise proof and infinite voters. *Journal of Economic Theory,* 2, 103-106.

Fishburn, P.C. (1989). Foundations of decision analysis: Along the way. *Management Science,* 35(4), 387-405.

Frank, I. E., & Friedman, J. H. (1993). A Statistical view of some chemometrics regression tools. *Technometrics, 35*(2), 109-135.

Fung, R.Y.K., Tang , J., Yiliu Tu, P., & Chen, Y. (2003). Modelling of quality function deployment planning with resource allocation. *Research in Engineering Design, 14*, 247–255.

Gardner, E.S. (1985). Exponential smoothing: The state of the art. *International Journal of Forecasting*, *4*, 1 – 38.

Gardner, E. S. (2006). Exponential smoothing: The state of the art - Part II. *International Journal of Forecasting, 22*(4), 637-666.

Garrett, T. A., & Leatherman, J. C. (2000). An introduction to state and local public finance. *The Web Book of Regional Sceinces*. Retreived from http://www.rri.wvu.edu/WebBook/Garrett/chapterfour.htm.

Green, P. E. & Rao, V. R. (1971). Conjoint measurement for quantifying judgmental data. *Journal of Marketing Research, 8*(3), 355-363.

Green, P.E. & Srinivasan, V. (1978). Conjoint *Analysis in Consumer Research*: Issues and outlook. *Journal of Consumer Research, 5*,103-123.

Green, P. E., & Srinivasan, V. (1990). Conjoint analysis in marketing: New developments and implications for research and practice. *Journal of Marketing, 54*, 3–19.

Haaland, D. M., & Thomas, E. V. (1988a). Partial least-squares methods for spectral analyses. 1. Relation to other quantitative calibration methods and the extraction of qualitative information. *Analytical Chemistry, 60*(11), 1193-1202.

Haaland, D. M., & Thomas, E. V. (1988b). Partial least-squares methods for spectral analyses. 2. Application to simulated and glass spectral data. *Analytical Chemistry, 60*(11), 1202-1208.

Hanke, J. E., Reitsch, A. G., & Wichern, D. W. (2001). *Business forecasting*. Upper Saddle River, NJ: Prentice Hall.

Hauser, J.R., & Clausing, D. (1988). The house of quality. *Harvard Business Review, 66*(3), 63–73.

Hazelrigg, G. (1996a). *Systems Engineering: An Approach to Information-Based Design*. New Jersey, NJ: Prentice Hall.

Hazelrigg, G. (1996b). The implications of Arrow's impossibility theorem on approaches to optimal engineering design. *Journal of Mechanical Design, 118*, 161–164.

Hazelrigg, G. (1998). A framework for decision-based engineering design. *Journal of Mechanical Design, 120*, 653–658.

Hazelrigg, G. (2003). Validation of engineering design alternative selection methods. *Engineering Optimization, 35*(2), 103–120.

Henseler, J., Ringle, C., & Sinkovics, R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing (AIM), 20,* 277-320.

Holt, C. C. (1957). Forecasting seasonals and trends by exponentially weighted averages. *International Journal of Forecasting, 20*, 5 – 13.

Horsky, D., Nelson, P., & Posavac, S. S. (2004). Stating preference for the ethereal but choosing the concrete: how the tangibility of attributes affects attribute weighting in value elicitation and choice. *Journal of Consumer Psychology, 14*(1-2), 132-140.

Hoyle, C. J., & Chen, W. (2009). Product attribute function deployment (pafd) for decision-based conceptual design. *IEEE Transactions on Engineering Management, 56*(2), 271-284.

Hoyle, C., Chen, W., Wang, N. X., & Koppelman, F. S. (2010). Integrated bayesian hierarchical choice modeling to capture heterogeneous consumer preferences in engineering design. *Journal of Mechanical Design, 132*(12), 121010.

Hsu, C. C., & Chen, C. Y. (2003). Applications of improved grey prediction model for power demand forecasting. *Energy Conversion and Management,44*(14), 2241-2249.

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*(4), 679-688.

Isukapalli, S. S., Roy, A., & Georgopoulos, P. G. (1998). Stochastic response surface methods (SRSMs) for uncertainty propagation: Application to environmental and biological systems. *Risk Analysis, 18*(3), 351-363.

Jo, H., Han, I., & Lee, H. (1997). Bankruptcy prediction using case-based reasoning, neural networks, and discriminant analysis. *Expert Systems with Applications, 13*(2), 97-108.

Jo, T. C., 2003. The effect of virtual term generation on the neural based approaches to time series prediction. *In the Proceedings of the IEEE fourth conference on control and automation*, Montreal, Canada.

Kandil, M. S., El-Debeiky, S. M., & Hasanien, N. E. (2002). Long-term load forecasting for fast developing utility using a knowledge-based expert system. *IEEE Transactions on Power Systems, 17*(2), 491-496.

Kayacan, E., Ulutas, B., & Kaynak, O. (2010). Grey system theory-based models in time series prediction. *Expert Systems with Applications*, *37*(2), 1784-1789.

Khan, K. B. (2002). An exploratory Investigation of new product forecasting pratices. *The Journal of Product Innovation and Management, 19*, 133-143.

Kim, W. J., Lee, J. D., & Kim, T. Y. (2005). Demand forecasting for multigenerational products combining discrete choice and dynamics of diffusion under technological trajectories. *Technological Forecasting and Social Change, 72*(7), 825-849.

Klimberg, R. K., Lawrence, K. D., & Lawrence, S. M. (2005). Forecasting sales of comparable units with data envelopment analysis (DEA). *Advances in business and management forecasting*, *4*, 201-214.

Kline, R. B. (2011). *Principles and Practice of Strutural Equation Modeling*. New York, NY: The Guilford Press.

Kolda, T. G., Lewis, R. M., & Torczon, V. (2006). *A generating set direct search augmented Lagrangian algorithm for optimization with a combination of general and linear constraints*, Livermore, CA: Sandia National Laboratories.

Kolmogorov, A. N. (1941). Stationary sequences in Hilbert space. *Bulletin of Mathematics-University of Moscow, 2*(6), 1– 40.

Kraus, S. J. (1995). Attitudes and the prediction of behavior: A meta-analysis of the empirical literature. *Personality & Social Psychology Bulletin, 21,* 58–75.

Krishnan, V., & Ulrich, K. T. (2001). Product development decisions: A review of the literature. *Management Science, 47*(1), 1-21.

Kuo, R. J., Chen, C. H., & Hwang, Y. C. (2001). An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network. *Fuzzy Sets and Systems, 118*(1), 21-45.

Kwong, C. K., Luo, X. G., & Tang, J. F. (2011). A multiobjective optimization approach for product line design. *IEEE Transactions on Engineering Management, 58*(1), 97-108.

Lancaster, K. J. (1966). A new approach to consumer theory. *The Journal of Political Economy, 74*(2), 132-157.

Lewis, C. D. (1982). *Industrial and Buisness Forecasting Methods*. London, UK: Butterworths.

Li, H., & Azarm, S. (2000). Product design selection under uncertainty and with competitive *advantage. Journal of Mechanical Design, 122(4), 411-418.*

Liao, S. H. (2005). Expert system methodologies and applications: A decade review from 1995 to 2004. *Expert systems with applications, 28*(1), 93-103.

Liu, S., Forrest, J., & Yang, Y. (2012). A brief introduction to grey systems theory. *Grey Systems: Theory and Application*, *2*(2), 89-104.

Liu, X., Zhang, W. J., Tu, Y. L., & Jiang, R. (2008). An analytical approach to customer requirement satisfaction in design specification development. *IEEE Transactions on Engineering Management, 55*(1), 94-102.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated Choice Methods Analysis and Applications*. Cambridge, UK: Cambridge University Press.

Luce, D.R., & Tukey, J.W. (1964). Simultaneous conjoint measurement: A new type of fundamental measurement. *Journal of Mathematical Psychology, 1*, 1-27.

Mahajan, V.E., & Wind, J. (1992). New product models: Practice, shortcomings and desired improvements. *Journal of Product Innovation Management, 9*, 128–139.

Makridakis, S. (1996). Forecasting: its role and value for planning and strategy. *International Journal of Forecasting, 12*(4), 513-537.

Marston, M., & Mistree, F. (1998). An implementation of expected utility theory in decision based design. *Proceedings of International Conference on Design Theory and Methodology DETC'98*, Atlanta, GA.

Mason, C. H., & Perreault, W. D., Jr. (1991). Collinearity, power, and interpretation of multiple regression analysis. *Journal of Marketing Research, 28*(3), 268-280.

Matzler, K., & Hinterhuber, H.H. (1998). How to make product development projects more successful by integrating Kano's model of customer satisfaction into quality function deployment. *Technovation, 18*(1), 25–38.

McFadden, D. (1999). Rationality for economists? *Journal of Risk and Uncertainty, 19*, 3-105.

McFadden, D. (2000). Disaggregate behavioral travel demand's RUM side: A 30-year retrospective. In D. Hensher (Ed.), *Travel Behavior Research. The Leading Edge* (pp. 17-63). Oxford, UK: Elsevier.

McIntyre, S. H., Achabal, D. D., & Miller, C. M. (1994). Applying case-based reasoning to forecasting retail sales. *Journal of Retailing, 69*(4), 372-398.

Monczka, R. M., Handfield, R. B., & Giunipero, L. (2009). *Purchasing and Supply Chain Management* . Mason, OH: South-Western Cengage Learning.

Muth, J.F. (1960). Optimal properties of exponentially weighted forecasts. *Journal of the American Statistical Association*, *55*(290), 299-306.

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied Linear Statistical Models*. Chicago, IL: IRWIN.

Newbold, P. (1983). ARIMA model building and the time series analysis approach to forecasting. *Journal of Forecasting, 2*, 23– 35.

Nicholson, W. & Snyder, C. (2008). *Microeconomic Theory Basic Principles and Extensions*. Mason, OH: Thomson Higher Education.

Pedersen, K., Emblemsvåg, J., Bailey, R., Allen, J.K., & Mistree, F. (2000). Validating Design Methods and Research: The Validation Square. *Proceedings of ASME Design Engineering Technical Conferences DETC '00*, Baltimore, MA.

Petiot, J. F., & Grognet, S. (2006). Product design: A vectors field-based approach for preference modelling. *Journal of Engineering Design, 17*(3), 217-233.

Quenouille, M. H. (1957). *The Analysis of Multiple Time-series.* London, UK: Griffin.

Petty, R. E., & Krosnick, J. A. (1995). *Attitude strength: Antecedents and consequences*. New Jersey, NJ: Lawrence Erlbaum Associates, Inc.

Rabikar, C. and Yoshi, S. (1990). New product introduction under demand uncertainty in competitive industries. *Managerial and Decision Economics,* 11(1), 1-12.

Ramdas, K., Zhylyevskyy, O., & Moore, W. L. (2010). A methodology to support product differentiation decisions. *IEETransactions on Engineering Management, 57*(4), 649-660.

Ramsey, F. P. (1931). "Truth and Probability" in The Foundations of Mathematics and Other Logical Essays, Routledge & Kegan Paul, London, 156-198. Reprinted in H. E. Kyburg & H. E. Smokler (1964). *Studies in Subjective Probability*, New York, NY: Wiley.

Ratner, R. K., & Miller, D. T. (2001). The norm of self-interest and its affects on social action. *Journal of Personality and Social Psychology, 81*, 5–16.

Reid, R. D., & Sanders, N. R. (2010). *Operations Management: An Integrated Approach*. Hoboken, NJ: John Wiley & Sons.

Savage, L. J. (1954). *The Foundations of Statistics*, New York, NY: Wiley.

See, T. K., Gurnani, A., & Lewis, K. (2006). Multi-attribute decision making using hypothetical equivalents and inequivalents. In K. E. Lewis, W. Chen, & L. C. Schmidt (Eds.), *Decision Making in Engineering Design* (pp. 145-154), New York, NY: ASME.

Simpson, T. W. (1998). *Concept Exploration Method for Product Family Design.* Retrieved from Georgia Institute of Technology Digital Dissertations.

Snyder, R.D. (1985). Recursive Estimation of Dynamic Linear Statistical Models. *Journal of the Royal Statistical Society*, *B. 47*, 272-276.

Steiger, J. H., & Schonemann, P. H. (1978). A history of factor indeterminancy. In S. Shye (Ed.), *Theory Construction and Data Analysis in the Behavioural Scinces* (pp. 136-178), San Francisco, CA: Jossey-Bass.

Suh, N.P. (1999). A theory of complexity, periodicity and the design axioms. *Research in Engineering Design*. *11*(2), 116-132.

Taguchi, G., Yokoyama, Y., & Wu, Y. (1993). *Taguchi Methods*. Dearborn, MI: American Supplier Institute Press.

Temme, D., Kreis, H., & Hildebrandt, L. (2010). A comparison of current PLS path modeling software: Features, Ease-of-Use, and Performance. . In V. E. Vinzi, W. W. Chin, J. Henseler & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 737-756). Berlin, Germany: Springer-Verlag.

Thevenot, H. J., Steva, E. D., Okudan, G. E., & Simpson, T. W. (2007). A multiattribute utility theory-based method for product line selection. *Journal of Mechanical Design, 129*(11), 1179-1184.

Thomas, E. V., & Haaland, D. M. (1990). Comparison of multivariate calibration methods for quantitative spectral analysis. *Analytical Chemistry*, *62*(10), 1091-1099.

Thurston, D. L. (2001). Real and misconceived limitations to decision based design with utility analysis. *Journal of Mechanical Design, 123*(2), 176-182.

Thurston, D. L. (2006). Multi-attribute utility analysis of conflicting preferences. In K. E. Lewis, W. Chen, & L. C. Schmidt (Eds.), *Decision Making in Engineering Design* (pp. 125-134), New York, NY: ASME.

Train, K. E., & Winston, C. (2007). Vehicle choice behavior and the declining market share of US Automakers. *International Economic Review, 48*(4), 1469-1496.

Tripsas, M. (2008). Customer preference discontinuities: A trigger for radical technological change. *Managerial and Decision Economics, 29*(2-3), 79-97.

Ulrich, K.T., & Eppinger, S.D. (2000). *Product Design and Development*, New York, NY: McGraw-Hill.

Vance, A., & Richtel, M. (2009). Light and cheap, netbooks are poised to reshape PC industry. *The New York Times*, New York, NY: New York Times.

van de Poel, I. (2007). Methodological problems in QFD and directions for future development. *Research in Engineering Design*, *18*(1), 21-36.

Velicer, W. F., & Jackson, D. N. (1990). Component analysis versus common factor analysis: Some issues in selecting an appropriate procedure. *Multivariate Behavioral Research, 25* (1), 1-28.

Vilares, M. J., Almeida, M. H., & Coelho, P. S. (2010). comparison of likelihood and pls estimators for structural equation modeling: A simulation with customer satisfaction data. In V. E. Vinzi, W. W. Chin, J. Henseler & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 289-305): Berlin, Germany: Springer-Verlag.

Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010a). Editorial: perspectives on partial least squares. In V. E. Vinzi, W. W. Chin, J. Henseler & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 1-20), Berlin, Germany: Springer-Verlag.

Vinzi, V. E., Trinchera, L., & Amato, S. (2010b). PLS path modeling: From foundations to recent developments and open issues for model assessment and improvement. In V. E. Vinzi, W. W. Chin, J. Henseler & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 47-82): Berlin, Germany: Springer-Verlag.

von Neumann, J. & Morgenstern, O. (1953). *The Theory of Games and Economic Behavior*, Princeton, NJ: Princeton University Press.

Wang, W. C., Chau, K. W., Cheng, C. T., & Qiu, L. (2009). A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series. *Journal of hydrology, 374*(3), 294-306.

Wassenaar, H. J. & Chen, W. (2003). An approach to decision based design with discrete choice analysis for demand modeling. *Journal of Mechanical Design, 125* (3), 490-497.

Wassenaar, H.J., Chen, W., Cheng, J., & Sudjianto, A. (2005). Enhancing discrete choice demand modeling for decision-based design. *Journal of Mechanical Design*, *127*(4), 514-523.

Wassenaar, H. J., Chen, W., Cheng, J., & Sudjianto, A., 2004, An Integrated Latent Variable Choice Modeling Approach for Enhancing Product Demand Modeling. *In the Proceedings of the ASME DETC/CIE 2004*, Salt Lake City, UT.

Weerahandi, S. & Moitra, S. (1995). Using survey data to predict adoption and switching for services. *Journal of Marketing Research, 32*(1), 85-96.

Widaman, K. (1993). Common factor analysis versus principal component analysis: Differential bias in representing model parameters? *Multivariate Behavioral Research, 28* (3), 263-311.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity*. Econometrica, 48* (4), 817–838.

Winters, P. R. (1960). Forecasting sales by exponentially weighted moving averages. *Management Science, 6*, 324–342.

Withanage, C., Choi, H. J., Duc, T. T. H., & Park, T. (2010a). Towards customer evaluation based product performance modeling. *In the Proceedings of the Industrial Engineering and Engineering Management International Conference IEEM 2010*, Macau.

Withanage, C., Park, T., & Choi, H. J. (2010b). A concept evaluation method for strategic product design with concurrent consideration of future customer requirements. *Concurrent Engineering, 18*(4), 275-289.

Withanage, C., Park, T., Duc, T. T. H., & Choi, H. (2011). Exploration of product value - characteristic relationship: partial least squares path modeling for product design and development. *In the Proceedings of the Industrial Engineering and Engineering Management International Conference IEEM 2011*, Singapore.

Withanage, C., Park, T., Duc, T. T. H., & Choi, H. (2012). Dynamic partial least square path modeling for the front-end product design and development. *ASME Journal of Mechanical Design, 134,* 100907.

Wold, S., Sjöström, M., & Eriksson, L. (2001). PLS-regression: a basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems, 58*(2), 109-130.

Womack, J.P., Jones, D.T., & Roos, D. (1990). *The machine that change the world: The story of lean production.* New York, NY: Rawson Associates.

Woodward, A. M., Alsberg, B. K., & Kell, D. B. (1998). The effect of heteroscedastic noise on the chemometric modelling of frequency domain data. *Chemometrics and Intelligent Laboratory Systems, 40*(1), 101-107.

Yeniay, O., & Goktas, A. (2002). A comparison of partial least squares regression with other prediction methods. *Hacettepe Journal of Mathematics and Statistics, 31*(99), 99-101.

Yule, G. U. (1927). On the method of investigating periodicities in disturbed series. *Philosophical Transactions of the Royal Society- London*, *226*(A), 267– 298.

Zhang, G. P., & Qi, M. (2005). Neural network forecasting for seasonal and trend time series. *European journal of operational research, 160*(2), 501-514.

APPENDIX

APPENDIX A. Yearly compact/mid Sedan market segment observations from 1990-2010

Year	Car Model Series
1990	METRO, TERCEL, EXCEL, ESCORT, SENTRA, MIRAGE,LEMANS, CAVALIER, SUNBIRD, SHADOW, SUNDANCE ,CORSICA BERETTA, TEMPO, ACCLAIM, CALAIS, PRIZM, COROLLA, TOPAZ, JETTA, CIVIC, PROTÉGÉ, SPIRIT, SKYLARK, GRAND AM, STANZA, NISSAN 240SX, LUMINA, INTEGRA, CAMRY, GRAND PRIX, ACCORD, SABLE, LEGACY, GALANT
1991	TERCEL, SHADOW, EXCEL, CAVALIER, MIRAGE, LEMANS, SENTRA, SUNBIRD, TEMPO, SATURN S, MUSTANG, CIVIC, SUNDANCE, SKYLARK, CORSICA BERETTA, PROTÉGÉ, SPIRIT, JETTA, COROLLA, GRAND AM, STANZA, MAZDA 626, TOPAZ, CAMRY, ACCLAIM, GALANT, INTEGRA, ACCORD, GRAND PRIX, NISSAN 240SX, SABLE, REGAL
1992	INTEGRA, CENTURY, REGAL, SKYLARK, CAVALIER, LUMINA, DYNASTY, SHADOW, SPIRIT, ESCORT, MUSTANG, TAURUS, TEMPO, ACCORD, CIVIC, PRELUDE, ELANTRA, EXCEL, MAZDA 626, PROTÉGÉ, TRACER, SENTRA, STANZA, ACHIEVA, SUPREME, ACCLAIM, SUNDANCE , GRAND PRIX, SUNBIRD, SATURN S, LOYALE, CAMRY, COROLLA, TERCEL
1993	INTEGRA, CENTURY, REGAL, SKYLARK, CAVALIER, LUMINA, DYNASTY, SHADOW, SPIRIT, ESCORT, TEMPO, ACCORD, CIVIC, ELANTRA, EXCEL, MAZDA 626, PROTÉGÉ, SABLE, TOPAZ, TRACER, ALTIMA, SENTRA, ACHIEVA, CIERA, SUPREME, ACCLAIM, SUNDANCE, GRAND AM, GRAND PRIX, SUNBIRD, SATURN S, CAMRY, COROLLA, TERCEL
1994	INTEGRA, CENTURY, REGAL, SKYLARK, CAVALIER, LUMINA, METRO, LEBARON, SHADOW, SPIRIT, ASPIRE, ESCORT, TEMPO, ACCORD, CIVIC, ELANTRA, EXCEL, MAZDA 626, PROTÉGÉ, SABLE, TOPAZ, TRACER, GALANT,

	MIRAGE, ALTIMA, SENTRA, CIERA, SUPREME, ACCLAIM, SUNDANCE, GRAND AM, GRAND PRIX, SUNBIRD, SATURN S, IMPREZA, CAMRY, CELICA, COROLLA, TERCEL, JETTA
1995	INTEGRA, CENTURY, SKYLARK, CAVALIER, CORSICA BERETTA, LUMINA, MONTE CARLO, CIRRUS, CONCORDE, AVENGER, NEON (DODGE), ASPIRE, CONTOUR, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, MAZDA 626, PROTÉGÉ, MYSTIQUE, SABLE, TRACER, GALANT, MIRAGE, ALTIMA, NISSAN 200SX, SENTRA, ACHIEVA, CIERA, SUPREME, NEON (PLYMOUTH), GRAND AM, GRAND PRIX, SUNFIRE, Saturn, LEGACY, CAMRY, COROLLA,TERCEL,JETTA
1996	INTEGRA, CENTURY, SKYLARK, CAVALIER, LUMINA, METRO, PRIZM, CIRRUS, INTREPID, NEON (DODGE), STRATUS SEDAN, ASPIRE, CONTOUR, ESCORT, ACCORD, CIVIC, ACCENT, ELANTRA, MAZDA 626, PROTÉGÉ, MYSTIQUE, TRACER, ALTIMA, SENTRA, ACHIEVA, CIERA, SUPREME, BREEZE, NEON (PLYMOUTH), GRAND AM, GRAND PRIX, SUNFIRE, SATURN S, LEGACY, CAMRY, COROLLA, TERCEL, JETTA
1997	CENTURY, SKYLARK, CAVALIER, LUMINA, MALIBU, PRIZM, CIRRUS, NEON (DODGE), STRATUS SEDAN, ASPIRE, CONTOUR, ESCORT, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, SEPHIA, MAZDA 626, PROTÉGÉ, MYSTIQUE, TRACER, GALANT, MIRAGE, ALTIMA, SENTRA, ACHIEVA, SUPREME, BREEZE, NEON, (PLYMOUTH), GRAND AM, GRAND PRIX, SUNFIRE, SATURN S, LEGACY, CAMRY, COROLLA, TERCEL, JETTA
1998	INTEGRA, CENTURY, CAVALIER, LUMINA, MALIBU, PRIZM, CIRRUS, NEON (DODGE), STRATUS SEDAN, CONTOUR, ESCORT, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, SEPHIA, MAZDA 626, PROTÉGÉ, SABLE, TRACER, GALANT, MIRAGE, ALTIMA, SENTRA, CUTLASS, BREEZE, NEON (PLYMOUTH), GRAND AM, GRAND PRIX, SUNFIRE, SATURN S, CAMRY, COROLLA, JETTA
1999	CENTURY, CAVALIER, LUMINA, MALIBU, METRO, PRIZM, CIRRUS, NEON (DODGE), STRATUS SEDAN, CONTOUR, ESCORT, FOCUS, TAURUS, ACCORD,

	CIVIC, ACCENT, ELANTRA, SONATA, SEPHIA, MAZDA 626, PROTÉGÉ, COUGAR, MYSTIQUE, SABLE, GALANT, MIRAGE, ALTIMA, SENTRA, ALERO, CUTLASS, BREEZE, NEON (PLYMOUTH), GRAND AM, GRAND PRIX, SUNFIRE, SATURN S, LEGACY, CAMRY, COROLLA, JETTA, PASSAT
2000	CENTURY, CAVALIER, METRO, PRIZM, CIRRUS, NEON (DODGE), STRATUS SEDAN, ESCORT, FOCUS, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, SONATA, SEPHIA, MAZDA 626, PROTÉGÉ, SABLE, GALANT, MIRAGE, ALTIMA, SENTRA, ALERO, NEON (PLYMOUTH), GRAND AM, SUNFIRE, SATURN L, SATURN S, CAMRY, COROLLA, ECHO, BEETLE II, JETTA, PASSAT
2001	CENTURY, DEVILLE, CAVALIER, MALIBU, PRIZM, SEBRING, SEDAN, NEON (DODGE), ESCORT, FOCUS, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, SONATA, RIO, SEPHIA, MAZDA 626, PROTÉGÉ, GALANT, ALTIMA, SENTRA, ALERO, NEON (PLYMOUTH), GRAND AM, SUNFIRE, SATURN L, SATURN S, IMPREZA, LEGACY, CAMRY, COROLLA, ECHO, BEETLE II, GOLF, JETTA
2002	CENTURY, CAVALIER, IMPALA, MALIBU, SEBRING SEDAN, NEON (DODGE), STRATUS SEDAN, FOCUS, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, SONATA, RIO, SPECTRA, MAZDA 626, PROTÉGÉ, SABLE, GALANT, LANCER (MITSUBISHI), ALTIMA, SENTRA, ALERO, GRAND AM, SUNFIRE, SATURN L, SATURN S, IMPREZA, LEGACY, CAMRY, COROLLA, ECHO, BEETLE II, GOLF, JETTA
2003	CAVALIER, MALIBU, SEBRING SEDAN, NEON (DODGE), STRATUS SEDAN, FOCUS, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, SONATA, OPTIMA, RIO, SPECTRA, MAZDA 6, PROTÉGÉ, SABLE, GALANT, LANCER (MITSUBISHI), ALTIMA, SENTRA, ALERO, GRAND AM, ION, SATURN L, IMPREZA, LEGACY, CAMRY, COROLLA, BEETLE II, JETTA
2004	AVEO, CAVALIER, SEBRING SEDAN, NEON (DODGE), STRATUS SEDAN, FOCUS, TAURUS, ACCORD, CIVIC, ACCENT, ELANTRA, SONATA, OPTIMA, RIO , SPECTRA, MAZDA3, MAZDA6, SABLE, GALANT, LANCER (MITSUBISHI), ALTIMA, SENTRA, GRAND AM, ION, CAMRY, COROLLA, JETTA

2005	AVEO, COBALT, NEON (DODGE), STRATUS SEDAN, FOCUS, ACCORD, CIVIC, ACCENT, ELANTRA, SONATA, OPTIMA, RIO, SPECTRA, MAZDA3, MAZDA6, GALANT, ALTIMA, SENTRA, ION, IMPREZA, LEGACY, FORENZA, CAMRY, COROLLA, JETTA
2006	AVEO, COBALT, MALIBU, SEBRING SEDAN, STRATUS SEDAN, FOCUS, FUSION, ACCORD, CIVIC, ACCENT, ELANTRA, SONATA, OPTIMA, SPECTRA, MAZDA3, MILAN, ALTIMA, SENTRA, G6, ION, SCION xA, IMPREZA, FORENZA, CAMRY, COROLLA, JETTA
2007	AVEO, COBALT, MALIBU, SEBRING SEDAN, FOCUS, FUSION, ACCORD, CIVIC, FIT, ACCENT, ELANTRA, OPTIMA, RIO, SPECTRA, MAZDA3, ALTIMA, SENTRA, VERSA, G6, ION, IMPREZA, FORENZA, CAMRY, COROLLA, YARIS, JETTA
2008	AVEO, COBALT, MALIBU, SEBRING SEDAN, AVENGER, FOCUS, USION, ACCORD, CIVIC, FIT, ACCENT, ELANTRA, SONATA, OPTIMA, SPECTRA, MAZDA3, MAZDA6, ALTIMA, SENTRA, VERSA, G6, AURA, SCION xB, IMPREZA, CAMRY, COROLLA, YARIS, JETTA
2009	AVENGER, FOCUS, FUSION, ACCORD, CIVIC, FIT, ACCENT, ELANTRA, SONATA, OPTIMA, RIO, SPECTRA, MAZDA3, MAZDA6, ALTIMA, SENTRA, VERSA, G6, IMPREZA, LEGACY, CAMRY, COROLLA, YARIS, JETTA
2010	AVEO, COBALT, MALIBU, SEBRING SEDAN, AVENGER, CALIBER, FOCUS, FUSION, ACCORD, CIVIC, FIT, ACCENT, ELANTRA, SONATA, FORTE, MAZDA3, MAZDA6, ALTIMA, SENTRA, VERSA, CAMRY, COROLLA, YARIS, JETTA

VITA

VITA

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PUBLICATIONS

- C. Withanage, T. Park, T. T. H. Duc, and H. Choi, "Dynamic Partial Least Square Path Modeling for the Front-end Product Design and Development," *ASME Journal of Mechanical Design, 134,* 100907, 2012.
- C. Withanage, T. Park, and H. Choi, "A Concept Evaluation Method for Strategic Product Design with Concurrent Consideration of Future Customer Requirements," *Concurrent Engineering*, vol. 18, pp. 275-289, 2010.
- C. Withanage, H. Choi, T. T. H. Duc, and T. Park, "Towards Customer Evaluation Based Product Performance Modeling," in *Proc. Industrial Engineering and Engineering Management (IEEM), 2010 IEEE International Conference* on, Macau, 2010, pp. 1967-1971. **Winner of Outstanding Paper Award.**
- C. Withanage, T. Park, T. T. H. Duc and H. Choi, "Exploration of Product Value - Characteristic Relationship: Partial Least Squares Path Modeling for Product Design and Development," in *Proc. Industrial Engineering and Engineering Management (IEEM), 2011 IEEE International Conference* on, Singapore, 2011, pp. 733-737.
- C.Withanage, T. Park, T.T.H. Duc and H. Choi, "Product Value Metrics and Value Characteristics Modeling" – **Presented** at *Norddesign Conference, Aalborg, Denmark*, 2012 (Aug).