Guiding New Product Development & Pricing in an Automotive High Tech SME:

When customer preferences are critical to strategic decisions using Conjoint Analysis adds needed precision to model formulation & validation

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Abstract

This paper describes the use of system dynamics in combination with conjoint analysis to assist a high tech SME in evaluating different policy options in a context where customer preferences were critical to strategic decision making. Conjoint analysis served an important role in eliciting customers' underlying multi-attribute choice preferences, and had a significant impact on both the structure and parameterization of the final simulation model. The combination of methods was quite powerful in this case and we feel could be successfully applied to a broad class of problems where behavioral policies of decision makers include tradeoffs among multiple attributes. In such cases, conjoint analysis- or other methods developed to address the multi-attribute choice problem- can add needed precision to model formulation and validation. The alternative is to use SD as a stand-alone approach and employ formulations that are not empirically derived or grounded in the extensive choice theory literature. We suggest this alternative is not viable when choice preferences are important for guiding strategic decisions, and more generally we contend that appropriately integrating relevant methods can substantially improve our system dynamics models and policy analysis.

Key Words: System dynamics, conjoint analysis, multi-attribute choice, new product design, automotive industry, product preference, multi-attribute utility function, Small & Medium Size Enterprises (SME)

1. Introduction-The Power of Combining Methods

Developing and introducing successful new products is crucial for the survival of most firms and particularly for small and medium sized enterprises (SME's). This paper describes the use of system dynamics in combination with conjoint analysis to assist a high tech SME in designing a new product for launch and in analyzing a number of different pricing strategies for the company's existing product. The system dynamics model was utilized within the company to rehearse these crucial strategic decisions. Conjoint analysis served an important role in formulating and estimating customers' decision policies and in guiding specification of model structure. The combination of methods was quite powerful in this case and we feel could be successfully applied to a wide range of issues where customer preferences are critically important in evaluating strategic alternatives.

The primary contribution of this paper is to provide a specific demonstration of how integrating modeling methodologies can significantly improve the formulation of system dynamics models and thereby improve policy analysis in supporting strategic decisions. It is our belief that system dynamics is too often employed as a stand-alone approach, and that there are substantial synergies from appropriately integrating relevant methods. We looked through each issue of the System Dynamics Review for the last nine years, and found very few articles discussing anything other than the application of system dynamics models in isolation. A related point, expressed by others previously, is that we should always strive to use numerical data and the appropriate statistical tools to ground our model formulations (Sterman, 2000 p. 854; Homer, 1997; Oliva and Sterman, 2001). We cannot cover the entire range of potentially complementary methods in one paper, so instead we describe one specific application, where combining methods proved valuable, that we believe can be applied to a broad class of problems. Specifically, we will discuss an application in which the behavioral policies of actors include making a choice involving trade offs between multiple attributes- a multi-attribute choice problem such as customer preferences for one company's products or services over rivals'. We argue that when multi-attribute choice preferences are critical to strategic decisions or important to overall model structure and/or behavior, modelers should make use of the extensive body of theory and empirical methods developed to address multiple criteria tradeoff problems.

Multi-attribute utility measurement has been combined with system dynamics in only a few previous studies available in the public domain. Nuthman (1994) discusses cognitive algebra and the use of judgment in model formulation, and identifies information integration as an area of research that system dynamicists should investigate to ground our cognitive formulations. Others have used multi-attribute utility measurement in field work to evaluate model generated policy options (Gardiner and Ford, 1980; Reagan-Cirincione et al, 1991); an application of the techniques that we feel should be more widespread. Homer (1996) mentions that he uses conjoint analysis, or data derived through conjoint analysis research conducted by the company, in a modeling project to explore product positioning in the pharmaceutical industry. However, he does not explain the use of conjoint analysis in the project since that was not the focus of the paper. We will try and fill this gap by describing in some detail how we combined system dynamics and conjoint analysis to significantly improve the formulation of our system dynamics model and thereby improve the subsequent policy analysis.

The next section provides additional background about multi-attribute choice problems, a commonly employed SD formulation for this class of problems, and an introduction to conjoint analysis. Section 3 focuses on a detailed discussion of the steps involved to effectively integrate SD and conjoint analysis by describing a modeling project with a high tech SME in the automotive industry. Section 3 describes a series of simulation experiments designed to help the SME's management team design a robust pricing and product development strategy. Finally, Section 4 discusses our findings and conclusions.

2. Background- Formulating an Attractiveness Index

Researchers from a variety of disciplines- economics, operations research, psychology, statistics, and marketing- have studied aspects of the multi-attribute choice problem. As a result, there are a variety of techniques to analyze choice preferences for situations in which a decision maker has to choose among options that simultaneously vary across two or more attributes. An enormous range of complex decision problems involve multiple conflicting objectives where the fundamental issue is one of value tradeoffs, and over the years a number of system dynamics models have addressed multi-attribute choice problems in various topic domains. Examples include models dealing with such diverse issues as new product diffusion in consumer and industrial contexts, urban dynamics, competition for market share in a variety of industries, competition in recruiting high quality staff, and the growth of alternative modes of transportation (Forrester, 1969; Piatelli et al, 2002; Backus et al, 2001; Mayo et al, 2001; Maier, 1998; Paiche and Sterman, 1993; Doman et al, 1995; Ford, 1995).

There is a long tradition in our field of incorporating attractiveness or relative attractiveness variables in our models to capture behavioral policies of actors trading off multiple attributes. These formulations are typically guided by the judgment of the modelers themselves, opinions of experts such as experienced managers in the industry, and readily available numerical data. This information is used to identify attributes important in the choice decision, and to specify formal mathematical relationships for the value tradeoffs across all attributes. These formulations often involve nonlinear attribute utility functions that are combined in a multiplicative attractiveness index. As one indication of how pervasive this piece of structure has become in our field, the Product Attractiveness Molecule[1] operationalizes this structure into a building block for the use of novice and experienced model builders (Hines, 1995). We do not suggest here that this formulation is wrong, and furthermore we applaud the efforts of those who have developed the molecules building-blocks as a resource library. However, when multi-attribute choice preferences are critical to strategic decisions or important to overall model structure and/or behavior, we contend that modelers should ground these formulations in the extensive choice theory literature and empirically derive underlying choice preferences. The consequences of not grounding these formulations are: 1) misspecifying model structure by ignoring important preference differences across decision makers, 2) inaccurate attribute utility functions that do not capture underlying preference structures, and 3) erroneous conclusions derived through policy analysis based on a flawed model. Employing conjoint analysis or another appropriate method developed to address the multi-attribute choice problem can add needed precision to model formulation and parameter estimation when choice preferences are critical to strategic decisions.

Conjoint analysis is actually a family of techniques and methods, all theoretically based on the models of information integration and functional measurement. The theoretical foundations for conjoint analysis are found in the seminal psychological research of

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[1] Molecules are available from http://www.vensim.com/molecule.html. From the tutorial distributed with Molecules 1.4: "Molecules are the building blocks of good system dynamics models. [Molecules]…provide a framework for presenting important and commonly used elements of model structure…"

Luce and Tukey (1964), and thousands of applications of conjoint analysis have been carried out over the past three decades by marketing scholars and practitioners. Conjoint analysis is, by far, the most used marketing research method for finding out how buyers make trade-offs among competing products and suppliers (Green, Krieger and Wind, 2001). To establish a model of customer judgments, conjoint analysis endeavors to unravel the value, or part-worths, that customers place on the product or service attributes from experimental subject's evaluation of profiles based on hypothetical products or services (Green and Wind, 1975; Green and Srinivasan, 1978 and 1990). The experimental design and the assumptions concerning the model form and types of relationships among variables are more important than the choice of estimation technique. To this end, conjoint analysis places more emphasis on the ability of the researcher or manager to theorize about the behavior of choice than it does on analytical technique for estimating part-worths.

Despite its popularity by marketing scholars and practitioners, conjoint analysis does not capture the 'market' dynamics of competition based on the underlying choice preferences. Different product concepts are 'tested' by parameterizing each concept along the full range of product attributes, and product attractiveness is computed based on the estimated part-worths. Predicted market share is then a function of the choice preferences, the hypothetical and/or actual product attributes, and scaling parameters to correct for intended versus actual purchase probability. Product attributes are not endogenous and the diffusion process over time is ignored entirely. Capturing the dynamics of the competition between firms is clearly important for evaluating policy options available to any individual firm in the industry, and this makes a persuasive case for combining conjoint analysis and system dynamics to get the best out of both approaches. We are not suggesting that every project with some aspect of choice preferences should use conjoint analysis or a similar method. Instead, we maintain that when model behavior is sensitive to choice preferences and policy recommendations are not robust in the face of relatively small changes in preference formulations, then conjoint analysis can add needed precision to formulations and increase confidence in the system dynamics model. The next section discusses, in detail, the steps involved in combining conjoint analysis and system dynamics in a modeling project with a high tech SME.

3. Combining System Dynamics and Conjoint Analysis

In Spring 2001, we conducted a modeling project with a high tech SME in the automotive industry. The SME, founded in 1994, was a fabless semiconductor manufacturer specializing in System-On-Chip networking solutions for information and entertainment systems to the automotive market. As the first company specializing in the nascent in-car network market, the SME enjoyed early success by introducing its technology, Digital Databus (D2B) Optical, at Mercedes-Benz in 1995. Further adoption by carmakers of D2B stagnated until 1998 when Jaguar Cars adopted the D2B technology for the new X-Type. However, the competitive landscape changed dramatically in 1998 as a rival company emerged and successfully introduced their technology (MOST) at BMW, Audi, Volvo, SAAB, and Daimler Chrysler. At the time our project began, there were two critical questions under evaluation by the SME's management team:

1) Should the price of the D2B solution be decreased in an effort to increase adoption of the technology by carmakers and what is the impact on the bottom-line?

2) What product attributes should the Company develop in their next generation platform and what is the likely market adoption of this new product?

Our modeling project got off the ground to help progress thinking about these issues and, ultimately, to propose specific policy recommendations that had the potential to substantially increase the value of the company.

3.1 Overview of the system dynamics model

The sector map in Figure 1 provides a high-level overview of the simulation model developed with the SME's management team to explore a variety of new product design and pricing strategies. There are four sectors representing: 1) the automotive industry, 2) our SME, 3) the competitor and 4) the market for in-car networks.

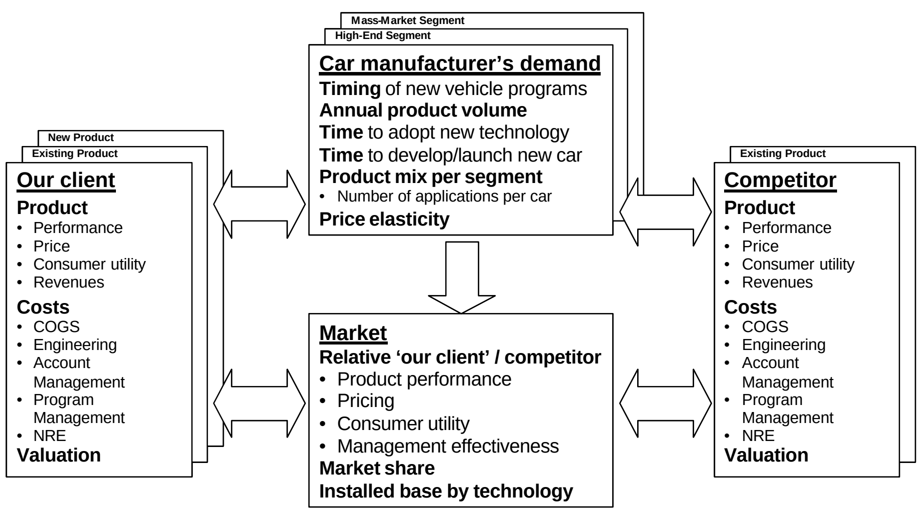

Figure 1: Model Sector Map

The automotive industry currently operates in a saturated market. In a struggle to differentiate car models, carmakers are expected to introduce a variety of new electronic devices that bring information and entertainment services, currently only available at the home or office, into the car. Some of this technology, designed to attract potential buyers, has already been adopted by some carmakers such as radar assisted cruise control, night-vision system, or voice control. Many industry experts suggest that within a couple of years new technologies will be standard in the vehicle – as common as the car-radio today. Examples of such technology include navigation and voice control systems and the ability to let passengers watch satellite fed movies or browse the Internet. As more of these in-car multimedia devices get bundled into the car, the automobile must be equipped with a digital network to facilitate information exchange between them.

The diffusion of these in-car multimedia networks across all carmakers is the primary area of concern for the project reported here. Since the focus of this paper is on the integration of system dynamics and conjoint analysis in this modeling project, we will only discuss the details of the model relevant to this integration process. Adoption of in-car networks by carmakers is crucial for the SME's strategic issues and is the point where the combination of methods proved quite valuable. The adoption process is discussed in the next section.

3.2 Adoption of in-vehicle networks

Carmakers make the decision to adopt an in-car network solution as part of the development process for a new vehicle. The pool of *Potential Automotive Partners* represents carmakers worldwide yet to adopt in-car networking technology, as shown in the stock and flow diagram in Figure 2. These potential partners may, over time, adopt an in-car networking solution and, upon adopting, become *Partners in Development*. Once the decision to adopt an in-car network for a new vehicle has been made, there is a substantial development delay before vehicle production. This delay is due to the development cycle of a vehicle, which usually takes up to three years in Europe, four years in the US and two years in Japan. The development partners, upon completion of the new vehicle development, become *Partners in Production* as the cars are launched into production. The *Technology Replacement Rate* represents carmakers phasing out vehicle programs and becoming potential customers again as they replace the technology in their next generation of cars.

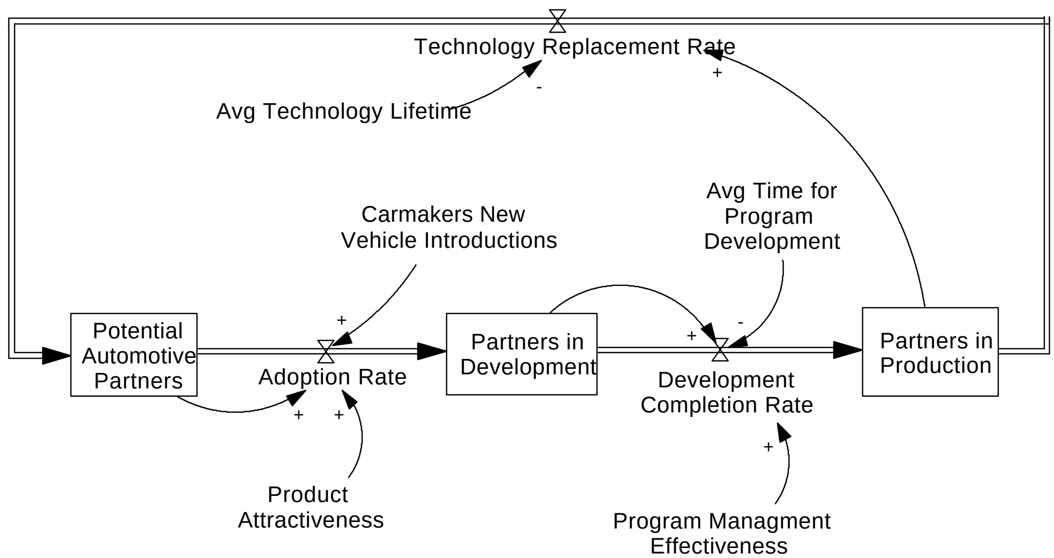

Figure 2: The in-car network technology adoption process

The *Adoption Rate* is dependent upon *Product Attractiveness* and *New Vehicle Introductions. New Vehicle Introductions* represents an assumption regarding the timing of new vehicle programs across all carmakers. There is considerable uncertainty about the launch dates of new vehicle programs, and we therefore assumed the market entry of new vehicle programs follows a normal distribution with mean and standard deviation derived from interview data with carmakers about the likely timing of new vehicles. Of course, carmakers may still not adopt an in-car network for their new vehicles if product attractiveness is below acceptable levels. *Product Attractiveness* is a multi-attribute measure of carmakers' preferences regarding the in-car network solutions available at any given time. Carmakers evaluate each in-car network based on multiple product attributes in deciding whether to adopt an in-car network and if so, which solution to adopt. These product attributes and the underlying choice preferences specifying the importance of each attribute were identified through market research, employing conjoint analysis, and are discussed in the next section.

3.3 Market research into product preferences

Suppliers in the automotive industry typically rely on concept testing to gauge prospective customer reactions to prototype product ideas. This approach yields valuable insights into the decision-making process of customers and reactions to a particular prototype product, but it does not provide quantifiable trade-offs for combinations of product attributes. For example, should the SME develop a 50Mbps product and sell it for $5 or a 100Mbps product and sell it for $10? Which combination creates more value?

In order to identify the product attributes carmakers considered in their choice of in-car network solution and to assess the value tradeoffs among these attributes, we employed the full profile conjoint analysis procedure to identify and measure carmakers' product attribute preferences for in-car networks. Surveys were sent to a large sample of industry decision makers, and respondents were presented with a set of product concepts containing the full range of product attributes. Respondents were asked to rank the product concepts according to their "attractiveness". The steps in a conjoint analysis are: 1) Identifying the relevant product attributes and designing the survey questionnaire, 2) Administering the survey and data collection, and 3) Estimating the underlying customer utility functions and identifying market segments. Each step is described in sequence in the following sections with details about how we implemented conjoint analysis in our modeling project with the SME.

3.3.1 Identifying Relevant Product Attributes and Survey Design

The first step in conjoint analysis is to identify the set of independent product attributes that are important to customers in making their choices about which products to adopt. A preliminary list of the important product attributes emerged from interviews with managers and employees of the SME who knew the product and market. These 'experts' identified five criteria that were subsequently discussed in another series of interviews with managers from carmakers, 1st tier suppliers, the IDB trade association, and microelectronics companies- a broad range of in-car network 'customers'. After this second round of in-depth discussions, one of the attributes was dropped from the initial list. These interviews were also used to identify the range of trade-off options for each of the product attributes. It is important in this step to be very clear about the implicit assumptions underlying the psychology of choice theory embedded in the selection of product attribute options. Findings from consumer behavior research indicate choice processes can be summarized as a two-stage process. In the first conjunctive stage, the consumer eliminates options with one or more unacceptable attribute levels. In the second compensatory stage, the options that remain are traded off on the multiple attributes (Lussier and Olshavsky, 1979). Following conventional conjoint study design, attribute levels were specifically chosen in our experimental design such that there were no unacceptable levels. Table 1 shows the final set of criteria and the available trade-off options.

Table 1: Product Attributes and Trade-off Options for the Market Research

Product Attribute / Research Criteria	Trade-off Options		
What is the required **bandwidth**?	20 Mbps	50 Mbps	100 Mbps
What is the preferred physical **transmission medium**?	Optical fiber	Unshielded Twisted Pair	Shielded Twisted Pair
What is an acceptable **node cost** for the network transceiver IC?	$ 5	$ 10	$ 15
Is it important that an **industry association** endorses the technology?	Yes	No	N/A

The next step in this process is to design a survey questionnaire that can be sent to (potential) customers for evaluation of the tradeoff options for all product attributes. Their evaluation of these tradeoffs will allow us to empirically estimate customers' underlying utility functions for each product attribute. The various options for all four product attributes result in a total of 54 separate product concept combinations[2], which would result in quite a lengthy survey if we presented subjects with all 54 concepts. Response rates tend to decrease with increasing questionnaire length, and more importantly, research indicates that long questionnaires may induce response biases (Lenk et al, 1996). To minimize the number of concepts presented to subjects, an orthogonal array experimental design (Addelman, 1962) was employed to select a small fraction of these 54 possible alternatives. Nine product concepts were selected that were sufficient to estimate all four attribute-level main effects on an uncorrelated basis[3]. It has been typical in conjoint studies to estimate only the main effects and assume away interaction effects, and we follow this convention. In certain cases, interaction effects may be important and in those cases the design must be adjusted to measure interactions.

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[2] The 54 possible product concepts are a result from multiplying the number of trade-off options per individual product attribute (54 = 3* 3 *3 * 2).

A pilot survey questionnaire was tested on a sample of ten experienced industry managers to determine whether the language and the instructions were clear. No additions or deletions occurred in the list of criteria as a result of this process, but some of the language describing the criteria was modified. It is important to clearly communicate the definition of each product attribute on the survey in order to minimize ambiguity in the respondent's mind concerning the trade-offs they are making. The nine different product concepts were finalized as shown in Table 2.

Table 2: Nine different product concepts to choose from

Product Concept No.	Supported Bandwidth	Supported Transportation Medium	Cost of the Network Node	Technology is endorsed as a industry standard
1	100+ Mbps	Shielded Twisted Pair (STP)	$15	Yes
2	100+ Mbps	Optical Fiber (POF)	$5	No
3	50 Mbps	Unshielded Twisted Pair (UTP)	$15	No
4	50 Mbps	Optical Fiber (POF)	$10	Yes
5	50 Mbps	Shielded Twisted Pair (STP)	$5	Yes
6	20 Mbps	Optical Fiber (POF)	$15	Yes
7	20 Mbps	Unshielded Twisted Pair (UTP)	$5	Yes
8	100+ Mbps	Unshielded Twisted Pair (UTP)	$10	Yes
9	20 Mbps	Shielded Twisted Pair (STP)	$10	No

3.3.2 Administering the Survey and Data Collection

After the survey questionnaire has been designed and pilot tested, the next step is to send the survey to a large and representative sample of (potential) customers. Survey research using unqualified leads typically yields a 2-3% response rate. We hoped to

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[3] The presence of interattribute correlation does not violate any assumptions of conjoint analysis. However, correlation among attributes increases the error in estimating preference parameters and should be kept to a minimum.

increase the response rate by using the SME's database of 500 industry and customer contacts. In an attempt to increase the response rate further, we decided to conduct the survey on the World Wide Web to make it easier for subjects to respond and to reduce the time needed to complete the survey. The survey was hosted on the SME's web site and also on the IDB-Forum web site. The IDB-Forum is an industry association that promotes the global integration of networking into vehicles, consumer electronics, and automotive electronics. The IDB-Forum contacted its members via phone and encouraged them to participate in the survey. Data gathering was confidential and anonymous. Respondents were asked to rank-order the nine product concepts, listed in Table 2, from one to nine- most (1) to least preferred (9). The choice of measure for customer preference need not be ordinal. The alternative is to obtain a rating of preference on a metric scale to obtain an indication of how much a customer prefers one product concept versus the others. As always, each preference measure has certain advantages and limitations. After two months of contacting and re-contacting respondents directly, 33 useable responses were received- a 6.6% response rate.

3.3.3 Estimating Attribute Preferences and Market Segmentation

The final step in conjoint analysis is to use the data from all completed surveys to empirically estimate customers' multi-attribute utility functions. Using respondents' rank ordering of product concepts, we can estimate part-worth utility functions for all product attributes using a modified form of analysis of variance specifically designed for ordinal data. In practice, we estimated the part-worths using multivariate ordinary least squares (OLS) regression[4] with the order-rankings for each product concept as the dependent variables and the different levels of each attribute as independent variables. This separate part-worth form is the most general, allowing for separate estimates for each level so that the data determines the type of relationship for each factor (i.e. linear or nonlinear). In the basic additive model, the most common in conjoint studies, it is theorized that the respondent simply "adds up" the values for each attribute (part-worth) to obtain the overall worth for a product concept. Let p = 1, 2, 3, …n denote the set of attributes used in the study design. Let y_{jp} denote the level of the pth attribute for the jth stimulus. The additive part-worth model assumes that the preference s_j for the jth stimulus is given by:

$$s_j = \sum_{p=1}^{n} f_p(y_{jp}) \tag{1}$$

where f_p is a function denoting the part-worth of different levels of y_{jp} for the pth attribute. Strictly speaking, part-worth functions are evaluated at discrete levels for each attribute, but interpolation is generally applied between levels of continuous variables.

After estimating the individual respondent utility functions using the additive part-worth model, the resulting individual respondent utility functions were subsequently used as an input into an unweighted pairwise cluster analysis. The cluster analysis was used to identify groups or clusters of respondents based on product preferences. Two clusters clearly emerged from the analyses – the "mass-market segment" including high volume manufacturers of low/medium and high-end cars such as VW, Ford, and GM, and the

[4] We later re-estimated these part-worths using Montonic Analysis of Variance (MONAVOVA), and found no significant differences.

"high-end segment", including lower volume manufacturers of medium and high-end cars such as Audi, Mercedes-Benz, and Jaguar. One representative individual utility function was selected for each market segment, and these representative part-worth utility functions for mass market and high-end segments are now discussed in detail[5]. In this case, we did not have a hold-out sample to test the accuracy of the model since this must be built in to the experimental design to collect data on additional product concepts. However, it is always preferable to evaluate model goodness of fit not only on the original stimuli, but also with a set of hold-out stimuli.

Part-worth estimates are on a common scale, and therefore we can compute the relative importance of each factor directly. In this study, part-worths have been scaled so that the lowest part-worth is zero within each attribute. The aggregate relative importance for the pth product attribute is represented by the range of the part-worth values for all stimulus levels (i.e. the difference between the lowest and highest value) divided by the sum of the ranges across all factors:

$$\text{Relative Importance}_p = \frac{\text{Range of Utility Values}_p}{\sum_{p=1}^{n} \text{Range of Utility Values}_p}$$

where n is the total number of product attributes.

Figure 3 shows the aggregate relative importance of each product attribute for the mass-market and high-end carmakers. It is obvious that the cost of a node on the network is the most important criteria for both market segments. After agreement on the

[5] All individual utility functions in each market segment were very similar. An alternative approach, and the one typically employed in conjoint analysis research, is to include all of the individual utility functions in the simulation model and compute market shares by aggregating the individual responses to the chosen stimuli.

importance of node cost, the customer segments diverge in the importance placed on the remaining product attributes.

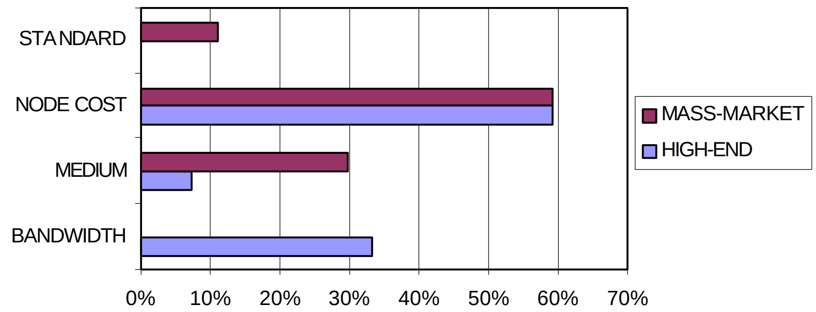

Figure 3: Relative importance of attributes for mass market and high-end segments

Figure 4 shows the node cost utility function for "mass market" and "high-end" companies- the function is identical for both market segments. A product that can achieve a node cost of around $5 achieves maximum utility. The other end of the spectrum at $15 is a "non-starter".

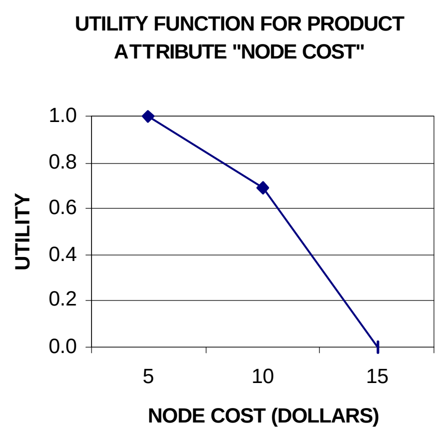

Figure 4: Node Cost Utility Function for the mass market and high-end segments

The differences between the two segments emerge in the utility functions for the remaining product attributes. We will discuss the mass-market carmakers utility functions on the remaining three product attributes, and then discuss the corresponding high-end carmakers utility functions. Space prevents us from including figures for all of the utility functions for each segment, but each utility function will be discussed.

For mass-market companies, the supported transmission medium is the second most important criteria with nearly all respondents preferring electrical over optical medium. The choice of transmission medium is driven primarily by ease of maintenance and Electromagnetic Compatibility (EMC) performance. Maintenance is generally considered easier for copper wire versus optical fiber. Shielded Twisted Pair (STP) and Unshielded Twisted Pair (UTP) are therefore easier to maintain than Plastic Optical Fiber (POF). On the other hand, poor EMC performance might interfere with other electronics such as the airbag or ABS system and also distort the FM radio band. POF is the preferred solution for minimizing EMC.

The third most important criteria for mass market carmakers is whether the technology is endorsed by an industry association, but this is much less important than Node Cost and transmission Medium. Mass-market carmakers prefer in-car network solutions that are endorsed by an industry association such as the Automotive Multimedia Interface Collaboration or the IDB Forum.

Lastly, and somewhat surprisingly, the supported bandwidth of a particular solution is not important to mass-market companies- the utility curve is flat at the value of zero. The survey gave bandwidth trade-off options in the range from 20 Mbps to 100 Mbps, and the finding that bandwidth is not important suggests that a bandwidth up to 20 Mbps is considered sufficient for mass-market companies.

For high-end carmakers, the maximum bandwidth offered by a particular product is the second most important criteria. The utility function is shown in Figure 5. These companies operate in the high-end, luxury segment of the car market and follow a differentiation strategy. Part of this strategy is to offer their customers “cutting-edge” technologies in their vehicles and typically these technologies require higher bandwidth. We can see that utility increases by 40% for products with 50 Mbps versus 20 Mbps. Above this point, the slope decreases somewhat, which indicates that a further increase is less important. A doubling of bandwidth from 50 Mbps to 100 Mbps only yields an additional 20% utility value.

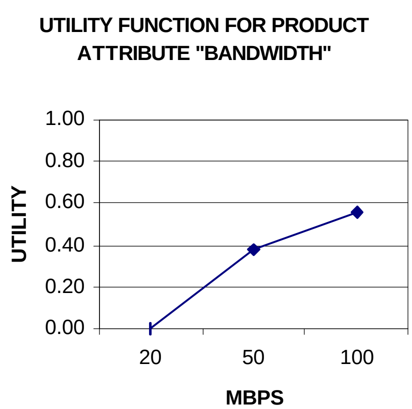

Figure 5: Bandwidth Utility Function in the High-End Segment

The supported medium is the third most important criteria for high-end companies, but is much less important than Node Cost and Bandwidth. In general, high-end companies have a preference for POF, and this preference can be explained by the perceived electromagnetic reliability of POF versus copper wire.

Finally, high-end carmakers do not attribute any additional value in products being endorsed by an industry association- the utility curve is flat at the value of zero. The rationale provided in some of the open-ended survey responses was that endorsement by an industry association might detract from the 'cutting-edge image' of the technology and dilute the differentiation benefits.

3.4 Integrating customer preferences into the system dynamics model

As a result of the market research, the management team gained crucial information about the product attributes that carmakers considered important and the tradeoff values among those attributes. Some of these insights about their customers' utility functions were altogether new for the management team or even went counter to their initial expectations. For example, the management team discovered that the market is clearly segmented and that some product features are not relevant for each market segment. In addition, one product attribute that management initially felt was quite important for carmakers was found to be unimportant in the choice preferences of both segments. With these new insights, the system dynamics model structure was modified to account for the two distinct customer segments, and the product attribute utility functions for each segment were incorporated into model.

The utility functions were operationalized into the system dynamics simulation model in the formulation for Product Attractiveness as shown in Figure 6[6]. This structure is

[6] The nonlinear utility functions can be implemented using graphical functions within Vensim, IThink or Powersim, or using table functions in the Jitia™ Simulation Software.

replicated for each of the two customer segments in order to reflect the different preferences in the “mass-market” and “high-end” segments.

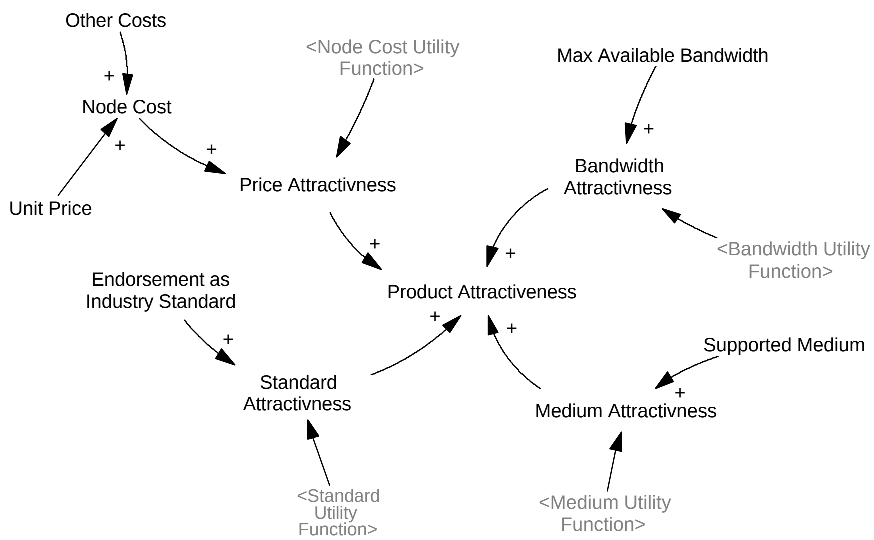

Figure 6: Product Attractiveness structure in the system dynamics model

Unit Price, Bandwidth, Transmission Medium and Endorsement from an industry association, are exogenous model parameters that allow the management team to experiment with different product concepts and pricing strategies to see how these changes impact the competition for market share over time. An exact replica of this structure is also operationalized for the competitor and is calibrated to reflect the actual product attribute levels of their MOST solution at the time of this study. Product Attractiveness is defined as the additive utilities of each individual product attribute.

The linear additive form is consistent with consumer behavior research on compensatory choice processes in which acceptable product options are traded off on multiple attributes (Lussier and Olshavsky, 1979). A number of studies have demonstrated the ability of the basic additive conjoint model to predict actual behavior

(Green and Srinivasan, 1990), and attribute levels were specifically chosen in the experimental design in this project such that there were no unacceptable levels. Adopting the additive form has an important implication for the system dynamics policy analysis. Specifically, it is clear that the operating conditions of the model are bounded by the acceptable attribute levels. Unacceptable attribute levels would take the model outside of its operating conditions and the resulting model behavior would not be reliable.

While the additive model has been the most commonly adopted form in conjoint studies, conjoint analysis is not limited at all in the types of relationships required between the dependent and independent variables. Alternative functional forms can be estimated using a wide range of conjoint methodologies (e.g. self-explicated, adaptive, or choice-based conjoint models), but the most important consideration is the experimental design to capture hypothesized decision making process. For example, Product Attractiveness formulations in SD models are typically multiplicative models of the decision making process. This formulation captures the conjunctive stage of the choice process where customers eliminate options with one or more unacceptable attribute levels (e.g. very high delivery delays or very low product quality). Conjoint analysis can certainly be used to estimate the multiplicative model using more complex statistical techniques[7], provided the collected respondents' evaluative data permits such estimations. In other words, the most important difference from the process described above is that the experimental design would need to be modified to ensure testing unacceptable stimuli and extreme attribute levels.

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[7] For example, using nonlinear regression to estimate the part-worths for each attribute level given the independent attributes are now multiplied to compute overall utility. Initial parameter values must be given to start the curve fitting process, and care must be taken to avoid local optima.

The resulting system dynamics model provided a solid framework to address the SME's key strategic questions. The next section discusses a number of simulation experiments designed to explore a variety of pricing and new product development policy options.

4. Simulation Results – Designing a robust pricing and product development strategy

This section describes how the system dynamics model was used with the SME's management team to address their strategic questions. The management team readily acknowledged that the SD model represented a quantum improvement in comparison to a spreadsheet based (financial) model in terms of exploring and evaluating strategic options. They now had a tool where their assumptions and the preferences of their end-customers were explicitly captured, and that could be used to explore the dynamic behavior of the market place. Some of the policy analysis insights contradicted their initial expectations about the policies that would add value for the firm. For example, counter to their previous beliefs, simulations demonstrated that decreasing the price of their existing in-car network solution to target on market segment and introducing a new product for the other segment can potentially double the value of the business. The following pages discuss a number of the simulation experiments.

4.1 Base-Case: Business as usual

The base case represents a reference simulation in which the model has been parameterized to reflect the competitive environment for the in-car network SME as of May 2001. At the time of this study, the worldwide market for in-car multimedia networking was split between two companies - the SME and one competitor. The SME currently offers the D2B optical solution and has developed a new solution, branded D2B Smartwire, which will be launched sometime in 2002. The SME's D2B technology has a specific bandwidth and transmission medium. These attributes are fixed as part of the design of the solution, and any changes result in the development of a new technology. Regarding the other product attributes, management directly controls the node cost, or price, and can certainly influence whether or not a trade association endorses the product. The competitor offers the MOST in-car network solution. The MOST and D2B product attributes for the base case are given in Table 3. It is important to note that product prices are not transparent, and therefore management made an assumption that the prices are equal to see the impact of the other attributes.

Table 3: Product attributes in the base case

Product Configurations	**MOST**	**D2B**
Max. Bandwidth	20 Mbps	6 Mbps
Supported Medium	POF	POF
Node cost	$ 10.59	$ 10.59
Endorsed as a standard	No	No

The time horizon of the model covers the 15 year period from 2001 - 2015 to include two vehicle lifecycles; one vehicle lifecycle is assumed to be six years on average. Figure 7 shows the adoption of D2B technology by carmakers including: a) *Potential Automotive Partners*, b) *Partners in Development*, and c) *Partners in Production*. The Base Case indicates a peak adoption rate for high-end firms in 2003, and mass-market firms do not enter the market at all. Gradual introduction for different vehicle models at one carmaker results in a partial *Automotive Partner* adoption rate. In the base case, our SME should expect to have approximately four automotive partners in production and two partners in the development phase by 2015.

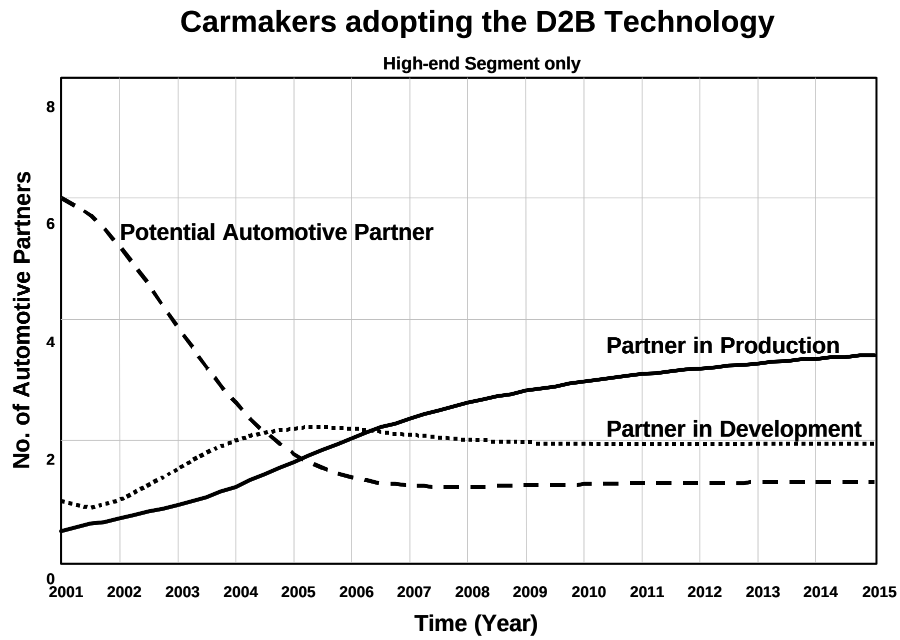

Figure 7: Base Case- Adoption of SME (D2B) Technology

The effects on Revenue and Earnings before Interest and Tax (EBIT) are shown in Figure 8.

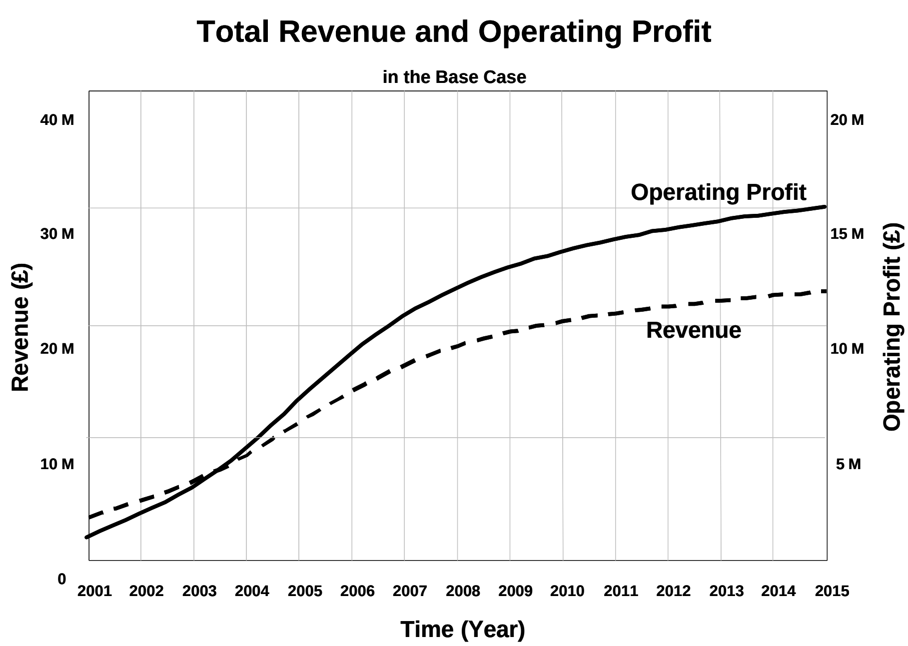

Figure 8: Base Case - SME Revenue and EBIT

The base case simulation clearly demonstrated to the SME's management that they would need to make a strategic move in order to reestablish their position as the leading in-car network company with carmakers. They had aspirations of capturing more than 50% of the 20 worldwide carmakers as partners, and the Base Case market share of 20% is a long way from that goal.

4.2 Penetration Pricing Strategy Targeting the Mass-Market Segment

The current products, D2B and MOST, have been primarily targeted at high-end carmakers, and are too expensive to extensively penetrate the mass-market segment. In fact, neither company has addressed the specific needs of the two distinct segments very effectively with the current products. During the two years from 1999 – 2001, the SME developed a new technology that will allow high data-rate transmission of signals via electrical cables. D2B SmartWire, the name for the new technology, will reduce system costs and better address the needs of the mass-market segment. However, our market research indicates that adoption by mass-market carmakers will be quite limited at current price levels.

Figure 9 shows that in the absence of a competing low price product, introducing D2B SmartWire as early as 2002 at a price of about $3 can successfully stimulate adoption by mass-market companies. In contrast to the base case, the penetration strategy results in a significant number of the mass-market carmakers adopting the D2B technology. The *Adoption Rate* peaks between 2005 and 2006 with slightly more than four carmakers entering the market. After the market becomes mature in 2010, there are on average 1.5 carmakers replacing the technology. Given no competition in the low price network solution, the SME could expect to partner with up to eight carmakers in production in the Penetration Pricing Strategy.

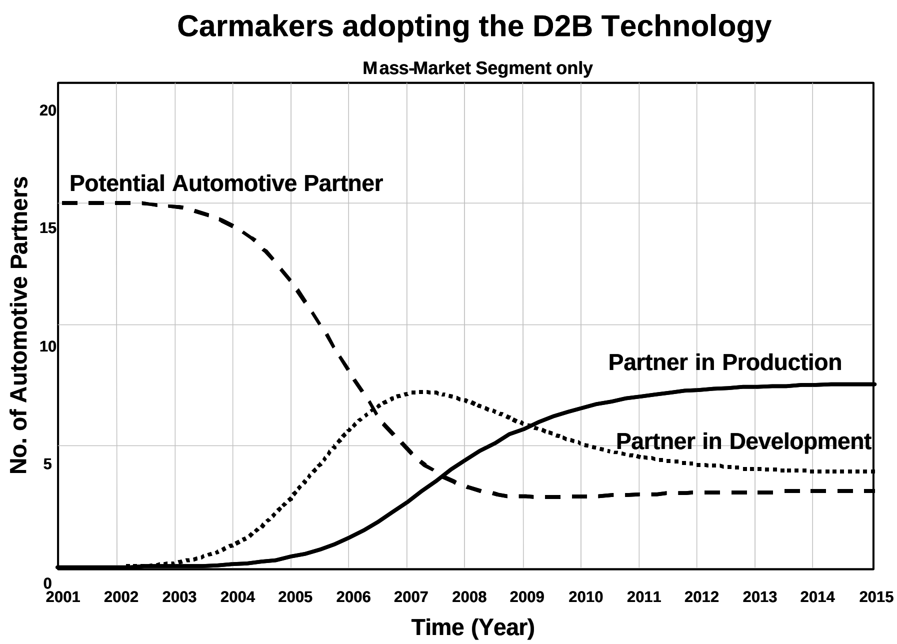

Figure 9: Penetration Pricing- Adoption of D2B Technology (mass-market segment)

There is a notable difference between the Base Case and this Penetration Pricing Strategy on the effect on the financials of the company- Revenues and EBIT triple. The impact of this strategy on EBIR is shown in Figure 10.

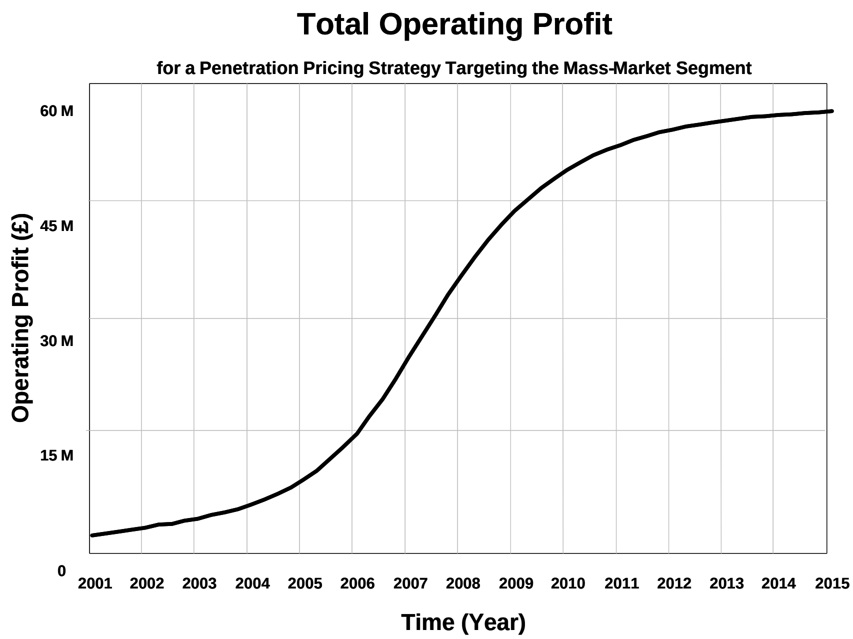

Figure 10: Penetration Pricing Strategy EBIT

4.3 New Product Development & Launch Strategy

The SME's current product offering, D2B Optical, is undifferentiated and does not offer sufficient bandwidth for high-end firms. At the same time, the solution is too expensive for mass-market firms. The Penetration Pricing Strategy just discussed enables the firm to open the mass-market customer segment with an extension of the existing product-D2B Smartwire. This leaves scope for new product development specifically targeting the high-end segment. Based on the insights from the market research and conjoint analysis, we worked with the management team to determine the 'ideal' attributes for a new product targeted for the high-end segment. This process suggested that the new product should offer a supported bandwidth of at least 50Mbps for a node cost of approximately $6 per unit. The transmission medium of the solution would be electrical instead of optical. This combination of product attributes maximizes utility given the constraints of the SME and the costs of the eventual product.

Given the lead times for new product development, we assume that such a product could be available in 2004. According to the utility functions obtained in market research, this product would become a clear segment leader with roughly 65% market share in the high-end segment. The availability of this new, superior product would result in a sudden increase in the high-end *Adoption Rate* by about 30%. In the long run, this results in a permanent increase in *D2B Partners in Development* and *D2B Partners in Production*. As shown in Figure 11, the New Product Development (NPD) & launch strategy results in improved revenue and EBIT.

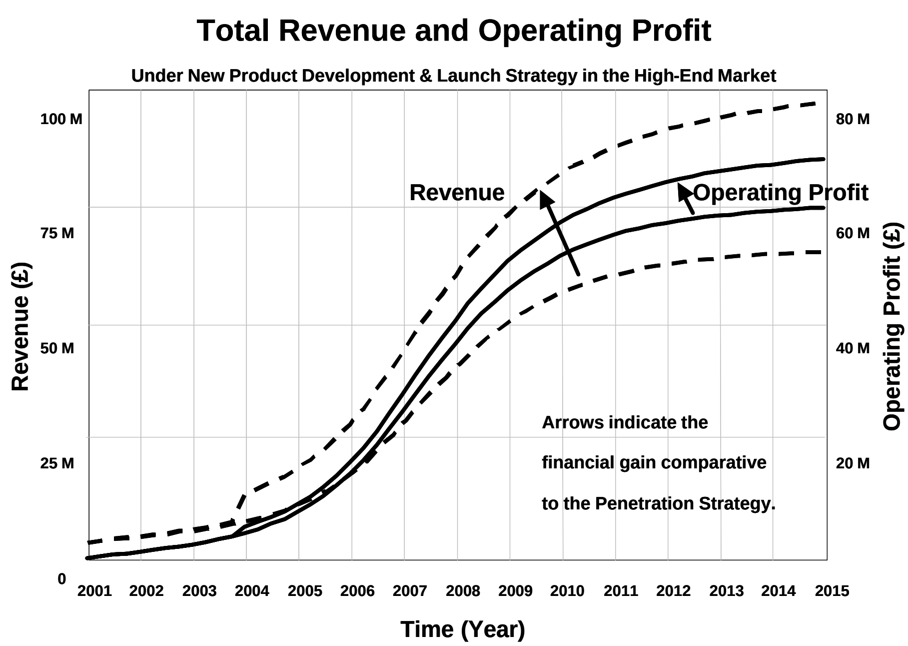

Figure 11: Financials for NPD & Launch Strategy in the high-end segment

5. Discussion & Conclusions

This paper provides a detailed step-by-step approach for integrating system dynamics and conjoint analysis to leverage the strengths of both. This process was illustrated through a modeling project in which we developed a small, high-level SD model of the automotive industry incorporating customer preferences derived through conjoint analysis to determine the success of competing products. In this case, management's information regarding customer preferences was quite limited and therefore it was absolutely necessary to do some market research in order to guide formulation of the system dynamics model. Perhaps this situation is more prevalent in SME's that have fewer resources to allocate to market research than large, established firms. Market research into customer preferences demonstrated that management's initial beliefs about the set of key attributes customers felt were critical and the relative importance of those attributes, were quite wrong. The market research had a significant impact on both model structure and parameterization. If the system dynamics model had been based only on management's judgments, the resulting policy analysis would have been erroneous and may have been harmful for the SME. The combination of methods proved persuasive with the management team, and resulted in a better system dynamics model and therefore improved insights for the company.

A number of tangible and timely recommendations emerged from the simulation experiments designed to evaluate different policy options. First, we simulated the current Base Case strategy of offering an undifferentiated product at a high-price point, and demonstrated the Base Case strategy offered minimum growth potential. After testing a variety of other policy options, we produced a new strategy for the SME automotive supplier that has the potential to double the value of its business. The first recommendation involved refocusing the existing product, by lowering the price significantly, to penetrate the large and growing mass-market segment. The second prong of this strategy focuses on introducing a new product to meet customer preferences in the high-end segment. It is quite clear that we could not have found robust and reliable quantitative answers to the SME's critical strategic questions by using a system dynamics model or a conjoint analysis market simulator in isolation. Integrating these methods unleashed substantial synergies, and we feel this combination could be successfully applied to a broad class of problems where behavioral policies of decision makers include tradeoffs among multiple attributes.

Of course, there are a number of open issues for future research to resolve about the process of combining these methods. The most important issue is clarifying the theoretical underpinnings of the choice process to guide our Product Attractiveness formulations as multiplicative, additive, or otherwise. Researchers in marketing, psychology and economics, now have a clearer understanding of multi-attribute decision making, but are still a long way from a consensus view on the best way to portray the choice process. We need to understand the contexts under which each formulation has an advantage in predicting choice behavior. As system dynamicists, we have been focused primarily on reference points and extreme attribute levels to guide our formulations for nonlinear utility functions. This process helps ensure our models are robust to extreme conditions tests, but may be sacrificing predictive power in the acceptable attribute range if we do not appropriately capture the compensatory tradeoff process among attributes. Another important issue for our community is to understand how often and under what conditions 'experts' judgments regarding customer preferences are unreliable. It may well be more often than we suspect, and in that case the importance of integrating an appropriate method for dealing with the multi-attribute choice problem becomes altogether more important. One last issue deals with the change in customer preferences over time. New technology is developed, unexpected industries converge, and social forces continuously shape cultural values. Perhaps the best way to handle these inevitable developments is by updating customer preference functions over time to keep abreast of shifts in choice preferences.

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