Diffusion of Technology Products that Keep Improving:
A Model for Forecasting New Adoption and Repeat Purchase Pre-Launch

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List of Abbreviations

ACA	-	Adaptive Conjoint Analysis
BEV	-	Battery Electric Vehicle
CA	-	Conjoint Analysis
CCD	-	Charge Couple Device
CP	-	Compare Pairs
CRT	-	Cathode Ray Tube
DSP	-	Digital Signal Processing
DVD	-	Digital Video Disk
EPRI	-	Electric Power Research Institute
GBM	-	Generalized Bass Model
HDTV	-	High Definition Television
HEV	-	Hybrid Electric Vehicle
I3A	-	International Imaging Industry Association.
ICE	-	Internal Combustion Engine
JPEG	-	Joint Photographic Expert Group
KWHr	-	Kilowatt Hour
LCD	-	Liquid Crystal Display
LMS	-	Least Mean Square
MB	-	Mega Byte
MP	-	Mega Pixel
MPEG	-	Moving Pictures Expert Group
NiMH	-	Nickel Metal Hydride
PC	-	Personal Computer
PI	-	Purchase Intentions
PMA	-	Photo Marketing Association
R&D	-	Research and Development
RMSE	-	Root Mean Square Error
RRMSE	-	Relative Root Mean Square Error
SDRAM	-	Synchronous Dynamic Random Access Memory
SE	-	Self Explicated
SLR	-	Single Lens Reflex
SUV	-	Sport Utility Vehicle
UD	-	User Design
VDSL	-	Video Digital Subscriber Line
WiFi	-	Wireless Fidelity
WOM	-	Word of Mouth

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Abstract

This thesis introduces a methodology that deals with the challenge of forecasting sales, including both new adoption and repurchase, and product (technology) evolution along the product lifecycle, pre-launch. The methodology is based on the mutual dependency between technology and the market. Future sales and product attributes are estimated endogenously by a dynamic model based on inputs given on market preferences, needs and purchase intentions on the one hand, and industry analysis on the other. The product attributes at launch are taken as the initial conditions for the dynamic model.

Technological progress, which leads to product improvements, encourages adoption and extends the market. Word of Mouth (WOM) and educative promotion also disseminate information about product features. For some products this information also motivates adopters to upgrade to more advanced versions. Growing sales motivate firms to invest in R&D and other product improvement strategies in order to leverage market opportunities. The interdependency between attribute improvements and sales makes the problem inherently dynamic. Estimating the dependency of attribute levels as a function of sales is based on a systematic industry analysis, considering the set of technologies used in a product and their trends, industry vertical and horizontal structure and their product development procedures and policies. The relating of market preferences and purchase intentions to attribute levels, which models the demand side, is based on data collected in a conjoint study. While in a common conjoint analysis respondents are requested to trade off quality and price, in our study we ask them to trade off quality and time. Customers who are willing to wait longer can purchase a better product at a better price. Those who need it earlier will need to compromise. Knowing the initial conditions at launch and the behavior models of the demand and supply side enables us to use iterations to generate a forecast of the outputs (i.e., sales for demand and attributes for supply) of each side.

The methodology involves introducing a dynamic model that leads to a forecast of sales and product evolution. We demonstrate how a speculated parameter set can generate a forecast that describes a rich set of sales dynamic patterns. The applicability of the methodology is demonstrated for the hybrid car and digital camera markets. The market data for hybrid cars were collected pre-

launch and some industry data were collected in the very early product introduction phase. The forecast for hybrid cars indicates that the transition from conventional cars, with internal combustion engines, to hybrid and electric cars will be quite quick. While hybrids with a modest all-electric range will be adopted first, more advance hybrids - and later electric cars - will finally dominate the market. Adopters of early hybrids will later switch to more advanced ones. We show that the major factor that will cause this rapid transition is the expected decline in the cost of batteries. The cost reduction path, which is estimated by our model, will be achieved by developing more efficient batteries and better manufacturing methods, based on the R&D activity of the relevant firms. The growing market, which serves as the main incentive for R&D activity, also provides the financial support for this activity. A sensitivity analysis presents how parameter variations change the forecast.

The data for the digital camera case were collected several years after launch in two phases. In the first phase we collected data about adoption in a conjoint study in 2004 and generated a forecast based on those data that could be collected pre-launch. We benchmark our forecast against other models and actual sales. We also forecast the development of camera upgrading trends based on initial repurchase patterns. The benchmark shows a good fit of the forecast to actual sales. We performed a second phase of market data collection in 2008 to capture actual repeat purchase patterns and used it to forecast future repurchase developments. Our findings indicate that the industry succeeded in adjusting its focus to the market's changing requirements and in driving repurchase due to obsolescence even when the market preferences shifted from the attributes that had caused adoption (such as resolution, service and memory), but had reached saturation, to new features (such as compactness, longer battery life, night photography and short delay between shots). We also found that the market has reached its peak and a slow decline in sales is expected. For digital cameras, which are repurchased not due physical wear-out but due to obsolescence, we could not base a repeat purchase forecast on data that could be collected pre-launch. A conjoint analysis can estimate the set of attributes that will drive a purchase, or, given that a product is already owned, what set will drive an upgrade. Still, in a pilot test we found that respondents could provide data about their next purchase, but not about two steps ahead, that is, they could not provide an estimation of the conditions that would drive them to upgrade an item before they had acquired the first one. The development of a method capable of capturing the attribute levels for an upgrade before the first version is adopted would enable a forecast of repurchase due to obsolescence pre-launch when used in our model.

Key words: Forecasting; Pre-Launch; Diffusion; Attribute Evolution; Utility; Conjoint-Analysis; Repeat Purchase; Technology.

1. Introduction

In the last decades, we have witnessed the evolution of several technologies, which have either revolutionized existing markets or created entire new markets in a very short period of time. Digital photography displaced film photography in the space of only a few years. Digital video, whether via cable, satellite, VDSL or DVD media, has practically replaced old analog video systems. Thin flat television screens, based on several competing technologies, have displaced CRTs. Personal computers, mobile phones, and broadband Internet are all relatively new markets that have evolved over a short period of time and have grown to giant scales. As mentioned by Gruppa and Stadlerb (2005), the rapid market growth was accompanied by both radical technological improvements and price decline. For products that failed in the market, such as the Video Laser Disk or the Iridium satellite phone, this simultaneous buildup of market and technological evolution simply did not occur. The ever-shortening lifecycles of new technology, as noted already by Mahajan et al. (1990), and the rapid market and technological changes present a challenge to common diffusion methods, which are based on sales data, since the time required for sales data collection is longer than the product’s entire lifecycle. The solution of pre-launch forecasting, which does not require sales data, was addressed by Urban et al. (1990) and Bass et al. (2001). A solution based on detailed spatial data at the very beginning of introduction was proposed by Garber et al. (2004). However, Urban's (1990) methods apply to a new brand in a well established market, where technological progress does not play a major role, rather than to the new product category. Bass et al. (2001) rely on market surveys only for potential market estimation while innovation and imitation are estimated by analogy. Garber et al.'s (2004) method relies on actual sales data in specific locations and cannot be implemented pre-launch.

Furthermore, a model to forecast sales of technology products needs to include an estimation of repeat purchase, due to physical wear-out and to obsolescence, in addition to adoption. While repurchase due to wear-out, explored by Olson and Choi (1985) and Kamakura and Balasubramanian (1987), is more significant at maturity and can be analyzed separately from adoption, repurchase due to obsolescence, mentioned by Bayus (1988) is linked to product improvements and has a significant impact also on growth. The PC market, whether of desktops or laptops, is a good example of a case where customers keep upgrading their products. Another example is the mobile phone market where adding new features and improving services push customers to buy newer phones although their current phones still work. In 2005 the sales volume of GSM mobile phones was 750M, but there were only 300M new subscribers. The other 450M phones were sold to customers who had purchased mobile phones in the past.

In the current work, we introduce a methodology that converts data collected pre-launch on both market and industry into a forecast of sales and attribute evolution over time. A major assumption of this methodology is the mutual influence of product or technological improvements on sales increase and vice versa. The data on technological progress procedures and drivers can be collected pre-launch, and are used to estimate the development of sales and product attributes. The interaction between the demand (sales) and supply (product/technology) sides was already recognized by Narasimhan (1989) and Loch and Huberman (1999). Narasimhan (1989) focused on the interaction between monopoly price strategy on the supply side and forward looking customers on the demand side. Loch and Huberman (1999), focus on the increased benefits to customers due to externalities which are influenced by the market size or installed base. Loch and Huberman (1999) also mention that market growth influences firms to invest in R&D and improve products, and that product improvement extends the market. However, these works do not show how to use these effects to estimate sales and product evolution.

We estimate the effect of market growth and repeat purchase on attribute improvements through R&D by using an industry analysis. Having assessed the attribute improvements through the industry response to market growth as described below, the effect of attribute improvements on market size is estimated by a conjoint analysis. The conjoint analysis is applied for varying attributes when the respondent trade-off adoption time and quality (i.e., earlier adoption of a basic product or waiting until a better product and price are available) rather than the common quality and price trade-off.

Assessing industry response to market growth in terms of product improvements involves the following steps:

1. Identifying the attributes desired by the market that can be provided by current or short-term, foreseen technology, with the aid of a focus group of customers, dealers and a technology expert.
2. Reducing the number of attributes and choosing the most relevant ones.
3. Identifying the technologies that support each feature (attribute) and distinguishing between technologies developed by product manufacturers and those supplied by third parties.
4. Breaking down the cost structure of the final product and assessing the portion of revenues from product sales that goes to each industry, taking into account the industry structure (monopoly or competition) as done by Ruggles (1955), and industry inter-relations.
5. Assessing the technology progress as a function of the R&D budget of each industry. The assessment considers industry procedures, described by Dahan and Hauser (2001),

technological progress assessment, as done by Moore (1965) based on the nature of a technology nature and an industry's past achievements, technology learning curves described by Grant (2002) and Söderholm and Sundqvist (2003) and specific industry standards and technologies as done by Nakajima (2001).

Product improvements drive not only adoption but also repeat purchase. We extend our model to forecast repeat purchase, driven by either physical wear-out or obsolescence. Our model refers not only to overall repeat purchase volumes, as done in previous repeat purchase research studies (see Mahajan et al. 1983; Olson and Choi 1985; Kamakura and Balasubramanian 1987; Bayus 1988; Fernandez 1999; Steffens 2002 and Gordon 2006), but also to attrition of older generations and substitution to newer ones.

The influence of product improvements, including augmented services and complementary products, on market growth has received solid support in prior studies (for a good review, see Lilien et al., 1992). On the other hand, growing market opportunities serve as a major incentive for firms to invest in improving the product, mainly through R&D investments (see Loch and Huberman 1999) and as a major justification for managers' R&D plans, as proposed by Bowman and Gatignon (2000). The announcement of Ofto's acquisition[1] by Kodak on May 2nd 2001 reflects the way in which managers consider market size when determining R&D spending decisions. We can also learn from Nikon's 2004 annual report (see Appendix A), which shows that the spending rate on digital imaging R&D was consistently around 4% of the preceding year's annual sales of the imaging product sector, which means that R&D for product improvements is influenced by sales. Telelogic's Focal-Point's management decision-supporting tool[2] demonstrates how the market attractiveness of each feature is weighed against the R&D cost required to add that feature. Such considerations have been a part of managers' decision-making processes for a long time; however, recently, following the development of tools such as Telelogic's Focal-Point, they have become part of the structured decision flow.

The forecasts generated by the proposed model include both sales development forecast and product attributes improvements forecast. These two related forecasts are significant for both marketing managers and product development managers.

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[1] Wednesday, 2 May 2001 04:00 GMT (ROCHESTER, N.Y.--(BUSINESS WIRE)
Kodak has today announced that it is acquiring Ofoto. Kodak, obviously realizing that a large chunk of their future is reliant on consumer digital imaging, has today signed a "definitive agreement" to buy the online photofinishing giant Ofoto. "The acquisition enhances our leadership in the growing market for online photo services. By combining Kodak's and Ofoto's technology, marketing and distribution assets, we will be able to deliver the most comprehensive, easy-to-use online photography services to customers and consumers," said Shih. "This will accelerate Kodak's growth and drive more rapid adoption of online photography."

[2] See details at http://www.telelogic.com/products/focalpoint/index.cfm

The implementation of our methodology for both new adoption and repeat purchases is demonstrated for the cases of the hybrid car and the digital camera.

The market data for hybrid cars were collected pre-launch and some industry data were collected at the very early product introduction phase. The forecast for hybrid cars indicates that the transition from conventional cars, with internal combustion engines, to hybrid and electric cars will be quite quick. While hybrids with a modest all-electric range will be adopted first, more advanced hybrids - and later electric cars - will finally dominate the market. Adopters of early hybrids will finally switch to more advanced ones. We show that the major factor that will cause this rapid transition is the expected decline in the cost of batteries. The cost reduction path, which is estimated by our model, will be achieved by developing more efficient batteries and better manufacturing methods, based on the R&D activity of the relevant firms. The growing market, which serves as the main incentive for R&D activity, also provides the financial support for this activity. A sensitivity analysis presents how parameter variations change the forecast.

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The current work is the first attempt to study quantitatively the mutual effect of market and product improvement, and use it for forecasting, and it anticipates making the following contributions:

1) Pre-launch sales and attributes evolution forecast for products that keep improving.

2) Identifying market segments (innovators, imitators) by their preferences. The conjoint analysis identifies the purchase intents of early adopters, who compromise on quality and price, and late adopters, who compromise on time.

3) A forecast of several generations that co-exist in the market without receiving the generations' launch time from the firms. The launch time is determined by market attractiveness and technological capabilities.

4) Adoption and repeat purchase forecast, including replacement due to physical wear-out and due to obsolescence.

5) Modeling "non-classic" diffusion curves such as chasm or saddle and other abnormalities.

Next, we review previous related works.

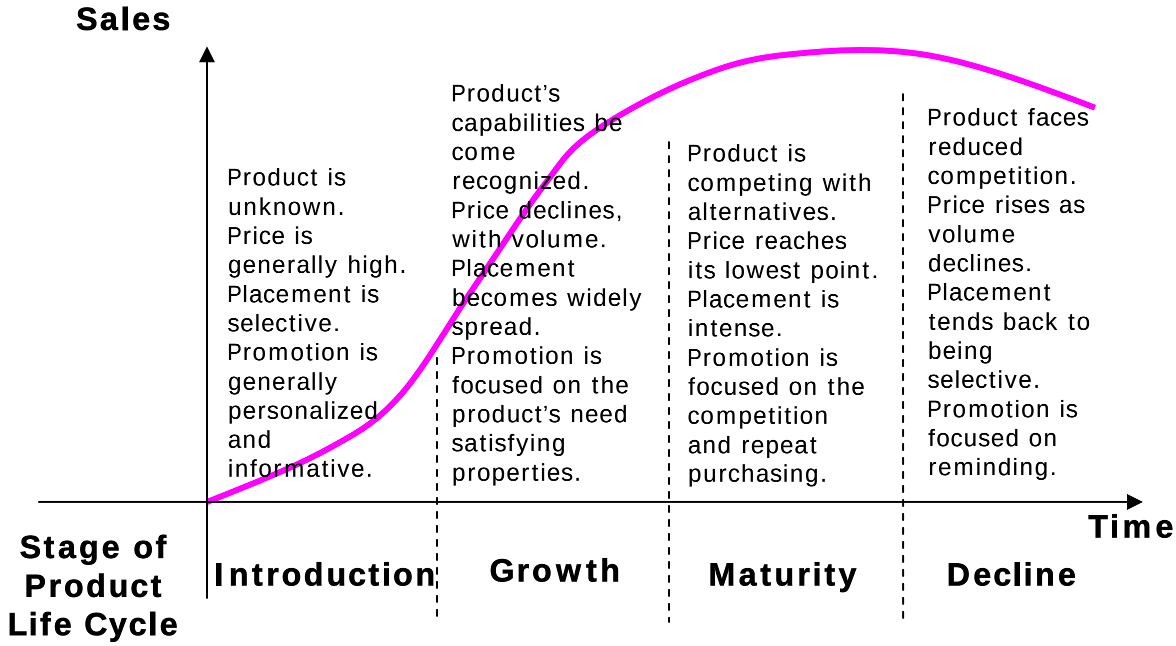
2. Previous Research

The following streams of literature are related to our research.

2.1 The Product Life Cycle Concept

The concept of products life cycle was outlined by Rogers (1962; 1983) and Levitt (1965). It describes the various stages that products, markets and industries go through thatare common to many products. A transition from introduction to market growth and then to maturity and finally decline involves, according to Rogers (1962; 1983) and Abernathy and Utterback (1978), many aspects and not only sales volumes. Rink and Swan (1979) and Tellis and Crawford (1981) describe other product lifecycle patterns such as revival, long maturity, and an oscillating market. The extended product lifecycle concept refers to many aspects, such as sales volumes, adopters' characteristics, product line diversity development and industry structure development. A common graphic description of sales development and product stages is presented in Figure 1. The method focuses on sequences and transitions that the product, industry and market experience, mostly in a qualitative way. The numeric description of the segments' sizes can be estimated retrospectively but cannot be used for forecasting. Its strength is in describing both a rich set of product lifecycle patterns and also many aspects of the product, industry and market rather than sales alone. We will show later how our concept uses a quantitative modeling of the product, industry and market processes, which we use it to generate a pre-launch forecast. We also show how long maturity and an oscillating market as well as other "abnormalities" such as a temporary decline in sales during market growth, often referred to a as chasm, can be modeled as well.

Figure 1: Product Life Cycle

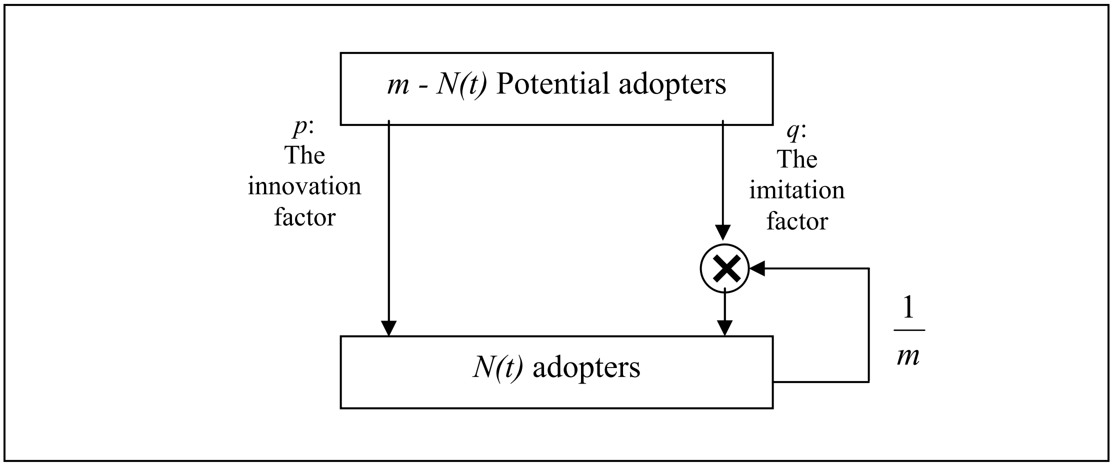


2.2 The Bass Model

Bass (1969) presented an analytic approach to product life cycle. The approach models the mechanism of the market dynamics and describes it by a differential equation (or by a difference equation for the discrete form). Once the parameters are known, system dynamics, or more specifically sales at each time, can be calculated by solving the equation analytically or numerically. A common notation is $N(t)$ for cumulative sales and $n(t) = \dfrac{dN(t)}{dt}$ for periodic sales. The Bass diffusion model is based on partitioning the target market into two groups, "Innovators" who are influenced mostly by the mass media and "Imitators" who are influenced by word-of-mouth. The basic model assumes that the influence factors on "Innovators" p and on "Imitators" q are constants. It also assumes that the target market m size is constant. The model deals with durable products that are purchased once. The model's parameters can be estimated by running a regression on sales data of several periods at the beginning of the product life cycle or by analogy to a similar product. Srivastava et al. (1985) and Bass et al. (2001) developed methods for estimating the diffusion parameters based on specific product attributes.

The diffusion scheme of the Bass model is detailed in Figure 2:

Figure 2: Bass model scheme



The Bass equation $\frac{dN(t)}{dt} = \left(p + q\frac{N(t)}{m} \right)(m - N(t))$ determines that the change in the total number of adopters, $N(t)$, is driven by the influence of media and word-of-mouth on non-adopters. Mahajan et al. (1990) find that there is a match between sales volumes as described by Rogers (1962; 1983) and Bass (1969). They review many of the Bass model extensions and mention that the model is widely used for forecasting innovation diffusion.

2.3 Generalized Bass Models

The Bass (1969) model describes the market growth using innovation and imitation coefficients that can be revealed only by regression from sales or by analogy. It maintains Rogers' (1983) concept that innovation is communicated through certain channels over time among the members of a social system. It does not refer explicitly to the influence of actual factors such as marketing mix or product improvements, including augmented services and complementary products, which according to Lilien et al. (1992) are the major drive for market growth. Bass's original model (1969) assumes that marketing mix is stable along the product's life cycle and that its influence is implicitly incorporated into the diffusion model's three parameters. Later studies, including those of Robinson and Lakhani (1975), Feichtinger (1982), Horsky and Simon (1983), Kalish (1985), Jones and Ritz (1991), Bass et al. (1994), Bass et al. (2000), Dockner and Fruchter (2004) and Shih and Venkatesh (2004) tried to capture the factors of the rich marketing environment, and their influence on sales in a more detailed model, and explicitly incorporated the influence of changes in the marketing mix in the diffusion model. Studies of the influence on adoption of changes in the product mix in general and in product attribute improvements in particular are numerous. Robinson and Lakhani (1975), Feichtinger (1982) and Dockner and Fruchter (2004) explored the influence of price changes on diffusion. Horsky and Simon (1983) and Kalish (1985) add advertising strategies and uncertainty reduction as factors that can alter diffusion rate. Jones and Ritz (1991) incorporate distribution or purchase convenience as a factor that influences diffusion. Bass et al. (1994) summarize many of the extensions and benchmark them against the original model. Shih and Venkatesh (2004) explore how a product's use patterns, or the match between the product's features and customers' needs, determine the market's development. The studies mentioned above are just some examples of research studies that refer to the influence of marketing strategies, or the "four Ps", on sales dynamics. There are many other studies that refer to marketing mix influence in the framework of diffusion theory. The common representation of the generalized Bass model, presented by Bass et al. (1994), is:

$$\frac{dN(t)}{dt} = \left(p + q\frac{N(t)}{m} \right)\left(m - N(t) \right) \cdot X(t),$$ where $X(t)$ represent the influence of the changes in the marketing mix over time.

The Bass model, as well as its generalized extensions, refers to the way that the market, or the demand side, is influenced by firms' activities and not to how firms are influenced by market developments.

2.4 Product Attribute Improvement

While firms' response to market developments, by altering promotion and distribution channels, and to some extent also price, can be executed relatively fast, the improvements of product features takes time and needs to be planned some time in advance. The influence of technological progress, or product improvements, on diffusion was previously addressed in diffusion-models for substitution of successive generations. Studies in this tradition include those of Norton and Bass (1987, 1992), Mahajan and Muller (1996), Islam and Meade (1997), Maier (1996), and Bass and Bass (2001). Norton and Bass (1987) refer to the inter-influence between generations and to potential market growth due to technological progress, and assume that the innovation and imitation coefficient remain stable across generations. Islam and Meade (1997) allow the innovation and imitation coefficient to vary between generations. Norton and Bass (1987) and Islam and Meade (1997) assume that the generation substitution timing, as well as the new generation features, are assumed to be determined by the manufacturers and given as an input for implementing the model. The aggregated sales of all generations sometimes sums into a classic diffusion curve, as shown by Bass and Bass (2001). In other cases, presented by Goldenberg et al. (2002), the aggregated sales curve may show a saddle. Another phenomenon, mentioned first by Goldenberg and Oreg (2007), is that generations may be skipped. As noted by Imai (1986) and David and Olsen (1986), the continuous process of improving the product within each generation has a significant impact. Studies on technology evolution and the influence of product improvements on customer decision, when the evolutionary path is obtained from external sources, were published by Weerahandi and Dalal (1992) and later by Schmidt and Druehl (2005).

2.5 The Role of Externalities

Some researchers indicate that the influence of the supply and of the demand side in not always uni-directional. A number of studies, including those of Katz and Shapiro (1985, 1986), Loch and Huberman (1999), Thun et al. (2000), and Haruvy et al. (2004) show that the effect of utility on customers depends on the installed base, due to direct and indirect externalities. An increased utility drives more customers to adopt the product and accelerates diffusion. In their models, the improvements in products benefits, due to externalities, are not obtained from external sources, as in generalized Bass models, but are calculated endogenously by the model. Externalities, as explained by Katz and Shapiro (1986) can be direct, where the customers benefit directly from the fact that others use the product, or indirect, where the growing installed base encourages firms and third parties on the supply side to offer better service. While direct externalities characterize mainly communication products, such as fax, mobile phones and internet terminals, indirect externalities are involved in almost any product. In some sense, the research of Kalish (1985), who explored the acceleration of diffusion due to uncertainty reduction caused by the expansion of the installed base, can be included in the externalities framework. In the models presented by Katz and Shapiro (1985, 1986) and Haruvy et al. (2004), the influence of externalities accelerates diffusion driven by traditional WOM. Loch and Huberman (1999) and Thun et al. (2000) show that diffusion can theoretically be based on the mutual influence of the demand and the supply sides, and can be explained by externalities, where WOM impact is omitted from the model. In their models the improvements in utility lead to market growth and market growth leads to utility improvements due to externalities effect.

2.6 Market Driven Product Improvements

The influence of the market on product improvements, which can also be included in the externalities framework, is mentioned in several studies. Bowman and Gatignon (2000) claim that managers frequently justify the development of new features and attributes as a means of attracting new buyers to a product category. Narasimhan (1989) refers to price declining strategies in a monopoly industry whose aim is to maximize profits by optimizing price and potential market. Narasimhan (1989) mentions that product improvement strategies may be influenced in a similar manner, but leaves this subject for future research. Loch and Huberman (1999) and Cerquera (2005) claim that R&D activities - once again product improvement activities - are not exogenous, but are influenced by the market. Stadler (1991) explored firms' R&D behavior over an entire product life cycle. He found that, under reasonable conditions, R&D activities increase in the early stages but decline when the market matures. When the market grows, firms accelerate R&D activity by adding resources and shortening schedules; when the market declines, firms cut R&D costs and delay the release of new models. The mutual influence between product improvement and market growth was also discussed earlier by Song and Chintagunta (2003), Söderholm and Sundqvist (2003), Karaca-Mandik (2004), and Sriram et al. (2006). They estimate the influence parameters on sales data using econometric methods. Pagani (2008) base a short-term forecast on that influence. She uses a very detailed model, which incorporates the mutual influence of market technology and industry structure, and demonstrates its implementation using the 3G mobile TV case. Song and Chintagunta (2003) mention that some customers are forward-looking and can predict the availability timing of better products. Being able to predict the introduction of new products shortens customers' response time, since some of the purchase preparations and actual processes can start before introduction. This is one of the reasons why, although it exposes plans to competitors, firms make pre-announcements of products that help customers to predict a product's launch time accurately. Similarly, as argued by Agarwal and Bayus (2004), forward-looking firms that predict market growth and allocate R&D resources earlier can gain an advantage in a competitive market.

2.7 The Role of Repurchase

Some researchers (Mahajan et al. 1990; Mahajan et al. 2000) compare the Levitt (1965) and Rogers (1983) descriptive model to Bass (1969) and followers' diffusion models which explain the mechanism that creates the product lifecycle sales curve. They refer to the match between the sales curves of the models at the market growth phase. However, the major difference, which is the long product maturity time characterized by repeat purchase domination in the descriptive models versus the short peak sales time in the diffusion models that focus on adoption, is practically ignored. Repurchase due to wear-out characterizes many products. Cars and washing machines are replaced after several years in service mainly because of wear-out. For products that last for a long time and evolve slowly, such as color TVs or washing machines, repurchase can be ignored until maturity Bass (1969). Then, since repurchase is mainly due to physical wear-out, sales stabilize at a rate depending on the average lifetime of the product. For many technological products that keep improving matters are different. Steffens (2002) notes that the dominant factor that characterizes long maturity time is repurchase, which is not included in the common diffusion models that refer to first purchase. Diffusion models usually ignore repurchase and focus on innovation, rather than on maturity. Fernandez (1999) presents a diffusion model that includes both adoption and replacement. Replacement in his model is modeled as a survival function which has normal distribution and matches replacement due to wear-out. The model incorporates both economic and demographic factors and yields a good fit of forecasting to actual sales of electric heaters in the US. Another diffusion model that incorporates both adoption and repeat purchase was presented by Bass and Bass (2001). Kaya et al. (2007) present a method for choosing the best repurchase distribution function and estimating the adoption and repurchase parameters and refers to repurchase due to obsolescence as well. Gordon (2006), who indicates that repurchase has attracted very little attention in the context of innovation, explored adoption and replacement in the PC market, where repurchase is driven mostly by obsolescence. The model includes a replacement behavioral model as a function of a product's attributes. He found that the replacement cycle, as well as the response to product improvements, has slowed down in the past decade. Repurchase due to wear-out was studied also by several other researchers (Lilien et al. 1981; Mahajan et al. 1983; Olson and Choi 1985; Kamakura and Balasubramanian 1987 and Fader et al. 2003) who refer mainly to stable products. Some of the generations substitution models, such as those of Bass and Bass (2001) and Goldenberg and Oreg (2007), refer to an upgrade to a new generation that is actually a repeat purchase driven by obsolescence.

2.8 Non Classic Diffusion Curves

The classic sales curve that describes a product's lifecycle has exceptions. Tellis and Crawford (1981) present some examples of "abnormalities" in the product lifecycle. Moore (1991) claims that a chasm, or a temporary decline in sales during market growth, is common. He explains the chasm by differentiating between the adopters segments at introduction, which are usually professionals, and the mass market. Goldenberg et al. (2002) explain the saddle phenomenon by the time difference in introducing new generations of a product. Van den Bulte and Joshi (2007) refer to different combinations of influences and imitators that can create various diffusion curves. Goldenberg et al. (2006) explore several empiric cases of saddles and present an analytic method, based on splitting the market into two segments, in order to model them. Our method can model more complex diffusion irregularities, mentioned by Rink and Swan (1979) and Tellis and Crawford (1981).

2.9 Forecasting Technological Evolution

Although technological progress is the dominant driver of diffusion of many products, forecasting technological progress is usually not discussed in diffusion literature. Predictions of technology evolution requires a thorough acquaintance with the technology and industry structure. In our model, since technological progress drives diffusion and is driven by the market, we refer to the technological evolution path as an inherent part of diffusion. We chose to deal with forecasting technology by using information about industry R&D procedures and methods, as in Dahan and Hauser (2001), Söderholm and Sundqvist (2003) and Nakajima (2001), and by analyzing firms' past performance. While R&D results, in terms of technological progress at the individual firm's level, are a function of creativity, innovation, efficiency and luck, at the macro level, as found by Yuan et al. (2007), R&D financial results, which are achieved by product improvements, are a function of investment. According to Dahan and Hauser (2001), this is particularly true for short- and mid-term R&D, which are financed by the business units and constitute the vast majority of firms' spending on R&D. Such R&D activity involves more converting an idea that is known and has been tested in a laboratory into a real product that can be marketed than developing a whole new idea. Long-term R&D, which has a higher uncertainty level, is usually financed directly by the corporation, but represents a very small portion of the total R&D expense. Support for Dahan and Hauser's (2001) claim that long-term R&D, with its high level of uncertainty and unclear timeline, is performed by small teams of experts and captures a small portion of the corporate R&D budget can be found in

Exhibit 1. For short- and mid-term R&D matters are different. Given an R&D budget, experienced managers can set specific technical goals and provide an achievable roadmap for technological progress. Managers can measure market trends and preferences for directing R&D efforts before actual sales by using market surveys or, after sales begin, by analyzing sales data. Moore (1965) envisioned mobile communication and personal computing without detailing a timeline. However, a very precise evolution path of electronic components technology which he presented then, known as "Moore's Law", is still valid today. Dahan and Hauser (2001) present the funnel theory, where long-term R&D examines many optional products. Long-term R&D is characterized by a high level of uncertainty and by low cost. As R&D progresses, the roadmaps converge into a few products, uncertainty is reduced, and costs increase. Grant (2002) explored many cases of industrial learning curves, where technological progress is driven by market success, and presents an analytic method to forecast short term technological progress. Söderholm and Sundqvist (2003) present the mutual influence of the market and the relatively mature technology of wind turbines. They propose a quantitative method of forecasting technological progress as a function of R&D investments. Nakajima (2001) demonstrates that for short-term R&D, where standards are stable and the industry structure is known, technological progress can be forecast in detail.

Theoretically, a surprising market success upon introduction might be too quick for firms to respond rapidly enough by improving the product. R&D activity takes time and there is a limit to how much the process can be accelerated. In practice, high demands should have been predicted by at least some of the firms, if reasonable marketing activity took place. As noted by Agarwal and Bayus (2004), forward-looking firms that predict market growth and allocate R&D resources earlier can gain an advantage in a competitive market. In addition, an unexpected demand would probably lead to a shortage, caused by production capacity limits along the supply chain, and create price pressures that would balance supply and demand. The common case scenario is when the market is built up gradually, accompanied by product improvements and price decline based on R&D. The price decline is made possible not so much by pricing strategy, as suggested by Schmidt and Druehl (2005), but rather by the reduction in costs achieved by mass production and by the development of innovative and more efficient manufacturing methods. Penetration pricing strategy for innovative technology products is avoided by initial high manufacturing costs, which are later reduced, based on R&D.

2.10 Pre-Launch Forecasting

Mahajan et al. (1990) note that by the time there are enough sales data observations for a reliable forecast based on the Bass model it is too late to use it for forecasting. Prior studies have dealt with the challenge of estimated diffusion based on data available in the early introduction or even pre-launch phase. Urban et al. (1990) focus on pre-launch sales forecasting of a specific new brand of an existing category in a highly competitive saturated market environment, where technological progress plays a minor (if any) role. Garber et al. (2004) use spatial detailed sales data to capture diffusion trends in the very early introduction phase, when sales volumes are still too low to estimate the diffusion parameters based on traditional aggregated level sales data. Bass et al. (2001) used a conjoint study to estimate the potential market; however, the rest of the parameters were estimated by analogy. Marez and Verleye (2004) and Schmidt and Druehl (2005) used market survey, including attribute improvements over time, to evaluate purchase intentions, assuming that the product evolution path is provided by the firms. Moe and Fader (2002) use advanced orders data which are available for some products.

3. Study Approach and Process

The method presented in this study refers to various aspects of the influence on the market of marketing mix changes, with a focus on product improvements, as well as various aspects of the influence of the market on firms' strategies, focusing on product improvements through R&D. We take a deductive approach, where we model the behavior of both the demand and the supply sides, based on their decision variables. The model uses some simplification assumptions and focuses on the dominant decision factors while dominated factors are ignored.

We consider a dynamic model that is based on the interdependency between attribute improvements and sales. The evolution of the sales over time, as a result of the product evolution, and vice versa, is based on both the customer purchase decision process (c.f. Weerahandi and Dalal 1992, Sriram et al., 2005) and the firm's decision process (c.f. Stadler 1991, Brouwer and Kleinknecht, 1999, Dahan and Hauser 2001, Pagani 2008). To find the dependency of attributes levels on adoption levels and repurchase patterns, we conducted an industry and technology analysis; to relate the adoption to attribute levels, we used data collected in a conjoint study. Repurchase due to physical wear-out is estimated based on the expected lifetime of the product under Olson and Choi's (1985) assumption that a worn-out product is replaced in a short time. Repurchase due to obsolescence is estimated based on products' characteristics, past replacements, and use patterns.

Our model considers the dependency of the motivation for improving the products and available resources for product improvement activities on market attractiveness or sales volumes, due to adoption and repeat purchase. The improvements in the product extend its potential market and drive users to upgrade their products. This mutual dependency creates the market dynamics.

We define a set of three assumptions, commonly accepted, which lead to the formulation of the model. We present the adoption model first and then extend it to include repeat purchase. The model is implemented first with speculated parameters. We demonstrate that complex product lifecycle patterns, and not only the classic s-shaped curve, can be described using a modest set of parameters. Then we implement the model on practical cases of the hybrid car and the digital camera.

We demonstrate the applicability of the model on the hybrid cars market, where on the demand side, we rely on market preference data that were collected in 2001. First we implement the model for adoption and then extend it to include repurchase. Industry response is estimated based on the past technological evolution path and on the interests and behavior of major players, including industry leaders, second-tier manufacturers, and new entrants. In addition, relations with components suppliers are also included. We forecast the technological progress of advanced hybrid and electric cars, which are not yet on the market, as well as the sales of both existing and future hybrids. We foresee that the transition from conventional cars with internal combustion engines to hybrid and electric cars will be quite quick. While hybrids with modest all-electric ranges will be adopted first, more advance hybrids - and later electric cars - will finally dominate the market. Adopters of early hybrids will finally switch to more advanced ones. We show that the major factor behind this rapid transition is the expected decline in the cost of batteries. The cost reduction path is estimated by our model. The cost reduction will be achieved by developing more efficient batteries and better manufacturing methods, based on the relevant firms' R&D activity. The growing market, which serves as the main incentive for R&D activity, also provides the financial support for this activity.

We also apply our methodology to the digital camera market, using market data collected at the end of 2004, for adoption forecast. To forecast repurchase we needed additional data which were collected in 2008. Product evolution was estimated based on the technological nature of the components that provide each feature and on actual product evolution at introduction and shortly after. The availability of actual sales data enables us to benchmark the quality of the forecast generated by our model. The results show a good fit of our model's forecast to actual sales for both adoption and repeat purchase.

In what follows, we first set up our model and present some theoretical implications. Next, we show how to implement the model for pre-launch sales forecasts on the hybrid car and digital camera, and discuss the results. We then conclude with suggestions for future research.

4. Model Formulation and Notation

In this section we formulate the model for forecasting sales that stem from both adoption and repeat purchase. First we develop the adoption model under the assumption that each customer purchases once. Then we release the assumption and adjust the model to include the influence of repeat purchase.

4.1 Diffusion of Durables – Forecasting Adoption

We consider a product with attributes that change with the number of users. Our consideration includes products that are characterized by direct network externalities, such as mobile phones, fax machines, e-mail, etc., but goes beyond this. We also include products with complementary services (indirect externalities), such as printer paper, memory cards for digital cameras, car insurance, video libraries for DVDs, etc. Both types of externalities are incorporated in earlier diffusion studies, such as Katz and Shapiro (1985, 1986), Loch and Huberman (1999) and Thun et al. (2000). Bowman and Gatignon (2000) and Cerquera (2005) argue that product attribute improvement can also stem from market acceptance as indirect externalities do since managers tend to invest in product improvements when market opportunities seem promising. Although, as claimed by Loch and Huberman (1999) and Thun et al. (2000), externalities can theoretically explain diffusion which does not depend on WOM, their impact on adoption is much weaker than the influence of product improvements. Narasimhan (1989) refers to price in a similar way. He claims that monopoly industries decide on a price declining path according to the potential market. As opposed to Narasimhan (1989), we do not require that the industry is monopolized and that customers are myopic. In our model the marketing mix, including price, service, distribution and product attributes, is directed by market needs in a competitive environment, which forces firms to improve a product's attributes and price. Customers are strategic and trade off between enjoying a product earlier or waiting for a better offer.

Following Sriram et al. (2006), we focus on how customers of high involvement products are influenced by the marketing mix. Knowledge of a new product category, as opposed to a specific brand in a competitive market, is usually not a limiting factor since it spreads fast. Sometimes, as in the cases of iPhone mobile phone, Chevy-Volt hybrid electric car, Alta-Vista operating system and many other examples, customers know details about the product before launch due to pre-announcements. The pre-launch WOM is not the classic imitation cause created by an adopter, since the product has not been launched at that time, but rather a discussion of the benefits of the product. As found by More (1988), when a product is launched potential customers decide whether to adopt and when, based on the match between their needs and the utility the product offers. We focus more on product features and price and less on other marketing mix dimensions such as promotion and place. We highlight the role of R&D as the major drive for market growth. R&D-based product improvements' influence is stronger and lasts longer than the influence of advertising or improvements of the distribution channels. Price decline based on cost reductions that stem from improved manufacturing methods is much more drastic than pricing policies based on cutting profit margins. Product improvements also cause positive WOM by adopters and potential adopters.

We have three basic assumptions that are consistent with broad empirical observations. The first assumption refers to consumers' motivation to purchase a product, the second to firms' motivation to improve their products, and the third to the dynamics of the level of adoption.

Assumption 1. One of the observed phenomena is that potential product adopters are influenced by the product's attribute levels (including accompanying services and price) and by the utility levels they enjoy from it (c.f. the conjoint analysis and product design literature). As a product's attribute levels improve, more customers want to adopt it. Let $A=A(t)$ be the vector of product attribute levels at time *t*, and let *m* be the potential adoption level (in percentages) of the product with attribute levels *A*. Then,

$$m=m(A). \tag{4-1}$$

Given that an acquisition is considered, *m(A)* represents the likelihood that consumers will choose the new product with attribute levels *A*, from among the alternatives, which also include buying an old technology or not buying at all. Similar to the studies of Weerahandi and Dalal (1992) and Loch and Huberman (1999), when the purchase consideration rate is $\alpha(t)$, the probability density of actually adopting the product with attribute levels *A*, say, Φ, will be

$$\Phi(A,t)=\alpha(t)\cdot m(A). \tag{4-1a}$$

We assume that, by the purchase consideration time, data about the product and its features have been collected by the customers through media, magazines, internet and word of mouth.

When the market is homogenous in attribute preferences, we can refer to the perceived utility of the product with attributes *A*, *u(A)*, not only at the individual customer level but also at the market level. In that case we can express the probability density of actually adopting the product as a function of the utility *u*.

$$\Phi(u(A),t)=\alpha(t)\cdot m(u(A)). \tag{4-1b}$$

In Eqs. (4-1a) and (4-1b), $\alpha(t)$ represents the *purchase consideration frequency (*or *rate)*, or the probability density of contemplating product acquisition at time *t.*[3] Note that when *t* refers to short periods of times, such as months, $\alpha(t)$ changes periodically with time due to seasonal effects, as mentioned by Radas and Shugan (1998); however, the likelihood of a customer considering a purchase during the period of one year, which is the integral of probability density within that time, is almost constant.[4]

The purchase consideration frequency $\alpha(t)$ is product-specific and may depend on the average lifetime of the product. For example, in the case of home appliances (washing machines, dishwashers, refrigerators, etc.) with a six-year[5] average lifetime, $\alpha=1/6$ when the rate is given per year or $\alpha=1/72$ when the rate is given per month. For seasonal products the rate is not the same

[3] The improving attributes have an influence on the alternative chosen but not on the decision consideration event itself. Thus $\alpha(t)$ is not a function of product attributes *A*.

[4] This assumption is realistic when the purchase stems from a customer's needs, as in our case when consumers are motivated by utilities or attribute improvements levels. For some products (such as home appliances or cars) purchase is considered when the old products are worn out. For other products (such as mobile phones or internet service) it is connected to contract expiration. There are products (such as MP3 and digital cameras) that are sometimes bought as a gift or a treat. Being linked to needs makes the likelihood of a purchase decision, when filtering out seasonal effects by referring to annual period, stable at the aggregated level.

[5] This is an arbitrary numeric example. Each product has its specific lifetime.

every month but can change from high to low and low to high and still maintain year-to-year stability. To estimate $\alpha(t)$ one can use market statistics about the products. For a radical new product, one will need to rely on market surveys, where customers are asked to estimate the time between the availability of a desired product and actual purchase[6] and take an average value. In the next section, we provide more details about the cases of hybrid cars and digital cameras. The value of $\alpha(t)$, when the time between the availability of a desired product and actual purchase is constant τ, for example, when the period is annual and neutralizes seasonal effects, is calculated as

$$\alpha(t) = 1/\tau \quad . \tag{4-1c}$$

To estimate the potential adoption level as a function of a product's attributes levels, *m(A),* one needs to use a conjoint study. There are many conjoint analysis methods. It is preferable to select a method that emulates the actual purchase decision process for the specific product. For products with high level of involvement and data collection prior to the purchase, such as cars, a full-profile or adaptive conjoint analysis (ACA) may be the best approach. For products , such as gadgets, where the decision is made at the store a choice-based conjoint (CBC) may be a better selection. For products that the user configures, like a PC, a user design (UD) method may be better. Other considerations which may influence the choice of the specific conjoint method are the number of attributes and levels, the sample size and the motivation of the respondents to fill out a long and detailed questionnaire. Often, it is useful to use a combination of conjoint methods to provide better accuracy and a cross check between the results.

As we will show in the next chapter, $m(A)$, or *m(u)* and *u(A)* can be assessed by conducting a conjoint study, while $\alpha(t)$ can be assessed by conducting a survey or by reviewing market statistics.

Assumption 2. Other observed phenomena (c.f. Loch and Huberman 1999, Bowman and Gatignon, 2000 and Cerquera, 2005) show that a growing market motivates firms and service providers to improve a product's attributes in order to deploy market opportunities. This leads us to the assumption that attribute levels depend on sales.

In our research, we focus on product improvements based on R&D. For many products, R&D, which is financed as a percentage of sales (see Brouwer and Kleinknecht, 1999), provides a powerful means for continuous and drastic product improvement. Other sources for product benefit improvements, such as direct and indirect externalities (see Katz and Shapiro, 1986), are also included in our model, but their influence is usually significantly weaker. Product improvements, as opposed to externalities, also encourage customers to upgrade their products. Unlike direct and

[6] This estimation may need to be verified by asking customers to detail their decision process explicitly and to detail the reasons for each step. This still needs to be scaled by stated-to-actual purchase ratio.

indirect externalities, estimating R&D results as a function of R&D efforts or budgets at the industry level requires analyzing the technology challenges and industry structure[7] and interrelations, as well as relations with other industries. At introduction, existing customers' preferences for existing technologies may lead customer-oriented firms to resist moving away from existing familiar or mature technologies (Adner 2002). Yet, new entrants and innovative firms may find market niches where the new technology has an advantage.[8] As the product improves and the market expands, hesitant firms tend to join the new technology trend and contribute to the technology's progress, in an attempt to defend their existing position. In the chapter 6 we show how to actually assess *A(f)* by conducting an industry analysis for the hybrid car and the digital camera cases .

Let $f=f(t)$ be the *cumulative adoption level* (in percentages), at time t, then,

$$A=A(f). \tag{4-2}$$

The probability density of actually purchasing the product with attribute levels A also becomes a function of f. More exactly, we have,

$$\Phi\left(A(f),t\right)=\alpha(t)\cdot m(A(f)). \tag{4-2a}$$

When the market is homogenous in attributes preference and utility evaluation the utility u, at the market level, becomes a function of f,

$$u(A)=u\big(A(f)\big)=u(f), \tag{4-2b}$$

and the probability density of actually purchasing the product with utility u becomes,

$$\Phi\big(u(f),t\big)=\alpha(t)\cdot m\big(u(f)\big). \tag{4-2c}$$

When the maximum potential market, of a certain product category, is M (in units), the relation between *cumulative adoption level* (in percentages), *f(t)* and *cumulative adoption market* (in units) *N(t)* is,

$$N(t)=M\cdot f(t). \tag{4-2d}$$

The value of M can be assessed, when running a conjoint study, using a screening question about the intentions of each respondent to ever use the product assuming best attributes, like Bass et al. (2001). For products that replace older technology in a mature market, like the transition from video cassettes to DVD or from film to digital photography the value of M can be estimated based on market statistics.

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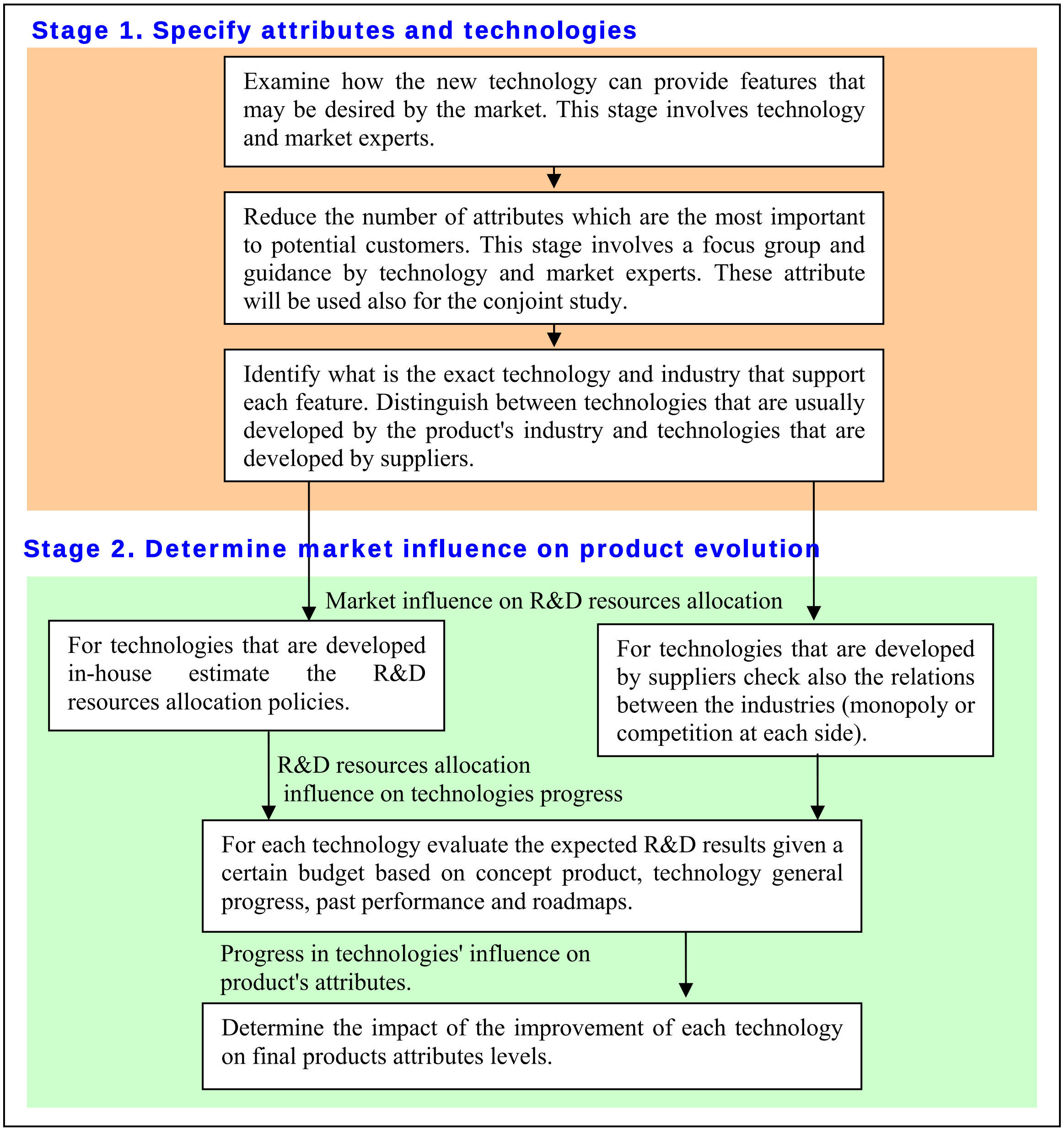
7 For example, a monopoly would improve the product only if elasticity justifies it. Since for many innovative products elasticity is high, monopolies tend to improve their products regularly. In the presence of competition, firms will improve the product also at low elasticity. Relations with suppliers, regulations and industry standards influence the attributes response as well.

8 For example, insurance agents and journalists, who needed instant results, were willing to compromise on the high price, poor quality and inconvenience of picture printing of digital cameras.

To assess *A(f),* which is product-specific in nature, one needs to perform an industry analysis. In Figure 3, we present general guidelines of how to analyze an industry's structure and inter-relations; in chapter 6 we show how to implement these guidelines for the hybrid car industry.

Figure 3: Industry Analysis Flow to Determine *A(f)*



Following Figure 3, in Stage 1, we specify attributes and technologies desired by the market. In Stage 2, we determine the effect of market development on the product evolution.

As mentioned previously, attractive markets motivate firms to improve products in order to leverage their potential. Klepper (2002) found that, as market growth accelerates, it attracts more firms. The growing market also finances R&D activity, as a percentage of sales,[9] which leads to further product improvements. In addition, product benefits improve due to indirect externalities (and some also improve due to direct externalities) but the major cause for product benefit improvements is R&D.

Estimations of industry response rely on industry and market analysis. The features required by the market and also used in the conjoint study need to be investigated by industry and technology experts to examine their implications for a product that incorporates a new technology. For example, the sound or voice quality of a mobile phone or the picture quality of a digital camera is linked to the embedded processor. One needs to estimate the required processor performance needed for each product's (camera or phone) quality levels and check its related implications in terms of cost, power consumption, and compactness.

After the technological implications of each feature have been identified, we need to check whether each component is usually manufactured within the industry or out-sourced. For example call-management software for mobile phones is developed by the handheld terminal manufacturers, while the modem software is usually provided by the DSP (Digital Signal Processor) components suppliers. We then need to evaluate how much R&D resources are expected to be directed to further development of each feature. Regarding technologies that are developed by suppliers, the influence of the specific product industry on its suppliers needs to be evaluated. The mobile phone industry has a strong influence on electronic component developers, due to its huge volumes. The digital camera industry, on the other hand, with much lower volumes, has to rely on developments driven by the mobile phone industry. The situation is different for industries that mainly serve the digital camera manufacturers. Until the emergence of digital photography, image sensor technology progressed very slowly, while other electronic components used in PC and mobile phones kept improving at a rapid pace. As digital cameras became common, image sensors started improving quickly, and the pace increased even more once mobile phones started to incorporate image sensors.

After estimating the amount of resources expected to be directed to further development of each feature, we need to assess the predicted outcome of this effort. This assessment is based on the nature of the R&D activity and the past performance of the R&D teams. The technological progress of electronic devices usually follows Moore's law[10] when backed with enough resources. To what extent a product line will be extended can be estimated given the resources that would be allocated to it and the cost of extending the product line by an additional item. Regarding mid-term development, there

[9] Competing firms who do not use the new technology yet need to allocate comparable resources to acquire it in order to protect their market position. These resources, raised from investors or firms' reserves and not from firms' sales, are determined by market opportunities.

[10] The rule formulated by Moore (1965) about electronic devices progress rate.

are usually specific standards, prototypes and concept models (see Nakajima 2001) for which managers are supposed to provide achievable roadmaps, thereby turning the models into marketable products. Within the context of allocated resources, we can use these roadmaps to assess how fast these models will be realized in market-available products.

Assumption 3. Let $\dot{f}(t) = \dfrac{df(t)}{dt}$ be the growth rate in the adoption fraction at time *t*; we assume that it will be equal to the probability density that the remaining fraction of potential adopters (untapped market), *1-f(t)*, will actually adopt the product with attribute levels *A*, at time *t*. Thus,

$$\dot{f}(t) = \Phi(f,t) \cdot (1 - f(t)), \qquad f(0)=0.^{11} \tag{4-3}$$

We can refer to a case where the market segments differ in their attribute preferences

$$\dot{f}(t) = \alpha(t) \cdot m(A(f(t))) \cdot (1 - f(t)), \qquad f(0)=0. \tag{4-3a}$$

or, for a case of homogenous product evaluation,

$$\dot{f}(t) = \alpha(t) \cdot m(u(f(t))) \cdot (1 - f(t)), \qquad f(0)=0. \tag{4-3b}$$

Note that in *Assumption 1*, we argue that customers are influenced in their adoption decision by the product attributes. They can learn about the product attributes from diverse sources, such as the Internet, advertising or from neighbors and friends. However, their decision as regards high involvement products is still influenced mainly by the perceived match of the product's attributes to their needs. This assumption is broadly supported in marketing literature (for a good review, see Lilien et al., 1992).

As Migdely (1976) found, information about the product spreads quickly but is not enough for convincing adoption. Awareness of new technologies is created by promotion, in the media, Internet and newspapers, and by WOM. This WOM is not necessarily from actual adopters. People talk about new technologies even when they have not adopted it yet or do not even plan to adopt. The awareness is a necessary pre-condition for adoption but not a sufficient one. The customer has to find a match between his/her need and the benefits offered by the product. This is the reason for focusing on the decision process, assuming that awareness is a given, rather than on communication. This is aligned with recent trends in marketing research as summarized by Muller et al. (2007). As Muller et al. (2007) note, the growing installed base can serve as a signal for uncertainty reduction, which does not require real social relations between adopters and potential customers. Actually we can refer to

[11] If instead of one configuration or brand we have a product line, *f(t)* becomes a vector and $\Phi(f,t)$ becomes a matrix.

the reduced uncertainty due to the growing market as an externality that saturates at modest[12] levels of adoption.

The model presented here integrates the customer's decision process (Eq. (4-1a)) and firms and service providers' response (Eq. (4-2)), see Figure 4.

Figure 4: Customer Adoption Decision and Firms and Service Providers Flow

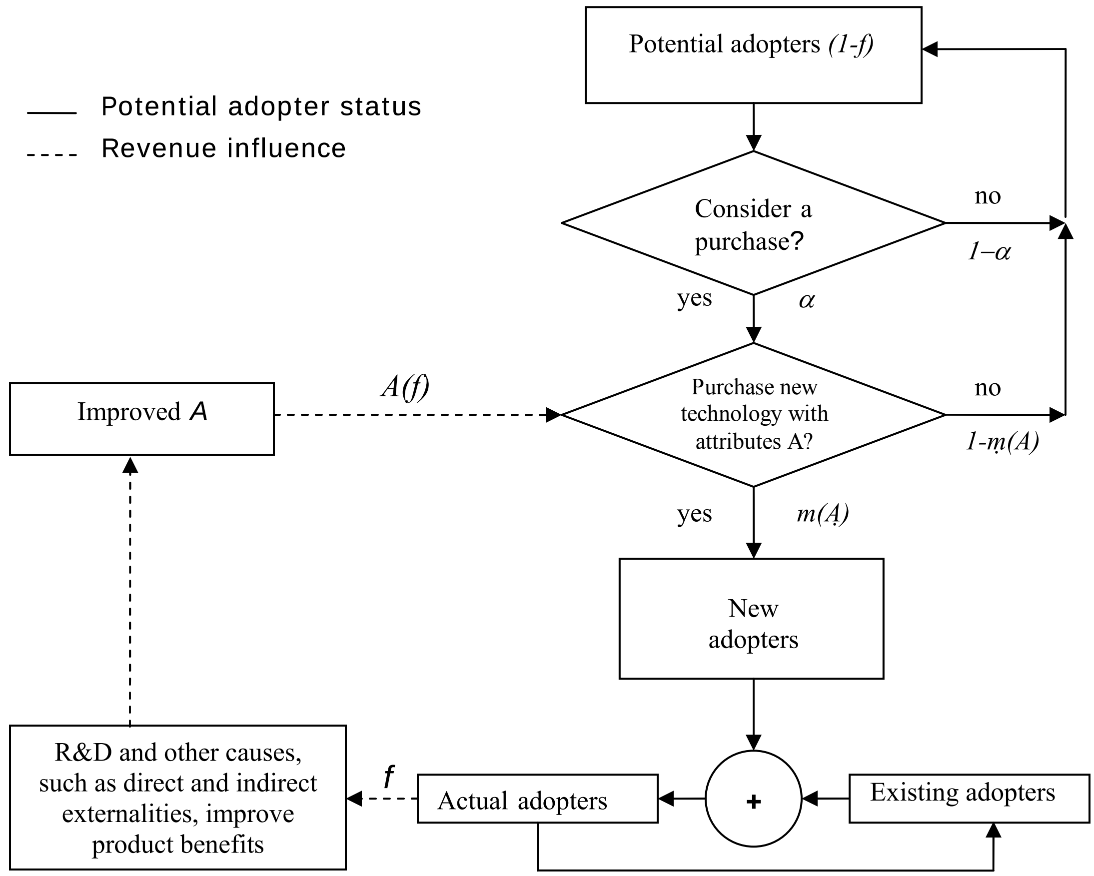


Figure 4 also incorporates the dynamics as a result of the influence of product attribute improvement on the market, and vice versa. Within the timeframe of one time period only a portion α of the potential market considers a purchase. The remaining share of $1-\alpha$ do not consider a purchase at that time, but may consider it at a different time; hence, they remain potential customers. From this portion, only *m(A)*, depending on attributes, will actually adopt the product. The other portion of *1-m(A)* will choose other alternatives. They may change their choice, when they reconsider a purchase, if the attributes of the product improve. The customers who decide to adopt change their status to that of 'actual adopters' joining the customers who previously became actual adopters. The flow of adoption diffusion as a result of customer decisions is represented in Figure 4 by a solid line,

[12] Usually it is enough to know that 10% of the market use the product to remove concerns about a new technology

as in the study of Weerahandi and Dalal (1992). The purchase of a product creates a motivation for product improvement and cash flow on the supplier's side. Some of the revenues are allocated to R&D, which improves the product and makes it a more attractive alternative when potential adopters consider a purchase. Other factors, such as direct and indirect externalities, influence actual benefits in the same way. The influence of sales on attribute improvements is represented in Figure 4 by a broken line.

4.2 The Role of Repurchase – Forecasting Adoption and Repeat Purchase

We refer to two types of causes for repurchase, *physical wear-out* and *obsolescence.* Repurchase due to physical wear-out was explored and modeled by Olson and Choi (1985) and Kamakura and Balasubramanian (1987). Bayus (1988) refers to obsolescence as a cause for repurchase. Mont (2008) presents empiric and theoretic support for the notion that replacement due to obsolescence is dominant for many products. Steffens (2002) and Kaya et al. (2007) mention upgrading as a cause for repeat purchase and incorporate repurchase in their diffusion models. However, since their diffusion models do not include utility, repurchase is modeled as a function of time rather than of attributes' improvements. Modeling upgrades as a function of time is problematic since, as found by Gordon (2006), the period until replacement may extend with time. We develop a method that models the customers upgrade decision, considering the utility that they can gain from their currently owned products versus the benefits they can gain from products that became available only after their previous purchase. More exactly, in the current research:

1. We follow earlier literature and assume that when a product breaks it is replaced in a short time so the quantity of disposals is the same as repeat purchase due to wear out.
2. We calculate the replacement rate at time t, as modeled by Olson and Choi (1985) and Kamakura and Balasubramanian (1987), by multiplying the quantities of past sales by the probability that the products stop functioning at time t.
3. We incorporate the impact of repeat purchase on adoption through the influence of the additional sales on product improvements.
4. We consider, in the case of repurchase due to wear-out, market dynamics when several generations co-exist. A customer who needs to replace an old product may decide to switch to a newer generation depending on the attributes of the alternatives at repurchase time. We incorporate the information of the products' attributes and the market shares of each in our model, to estimate not only the overall repurchase quantities but also the transitions between generations.

Next we present two models: the first incorporates repurchase due to wear-out and the second incorporates repurchase due to obsolescence (or upgrade). For simplicity, we assume that for each product one of the repurchase causes is dominant and the other can be ignored. Thus repurchase is either a replacement, driven by wear out, or an upgrade driven by obsolescence, but not both.

4.2.1 Repurchase due to Wear-Out

We will first present a model for a single product in the market then extend it to a case where several products in a product line or several generations coexist and share the market.

4.2.1.1 Repurchase due to Wear-Out with a single product

We will use the following notations for the case of a single product:

$f^{w}(t)$ = the cumulative market acceptance (in percentage) at time *t*, that stems from adoption, when there is repurchase due to wear-out.

$r^{w}(t)$ = the periodic repurchase sales (in percentage) at time *t* that stem from a product ceasing to function (wearing out) and needing to be replaced.

$s^{w}(t)$ = the periodic overall sales (in percentage) at time *t*, that stem from either adoption or repeat purchase due to wear-out.

$P(\tau)$ = the likelihood that the product is worn out and needs to be replaced after τ time periods in service.

$A^{w}(t)$ = product's attributes set levels at time *t* influenced by sales incorporating the effect of repurchase due to wear-out.

Similarly as in Eq. (4-1), the potential adoption level (in percentages) of the product with attribute levels $A^{w}(t)$, will be $m\left(A^{w}(t)\right)$. Also , given that an acquisition is considered, $m\left(A^{w}(t)\right)$ represents the likelihood that consumers will choose to adopt the new product with attribute levels $A^{w}(t)$ from among the alternatives, which also include buying old technology or not buying at all, given that a purchase is considered. As in the case of adoption, when the purchase consideration rate is $\alpha(t)$, the probability density of actually adopting the product with attribute levels $A^{w}(t)$, will be $\alpha(t) \cdot m\left(A^{w}(t)\right)$

In the presence of repurchase, firms are influenced in their product improvement activities not only by adoption $f^{w}(t)$ but also by the sales volumes that stem from repeat purchase $r^{w}(t)$. Thus, $A^{w}(t) = A(f^{w}(t), r^{w}(t))$. Note that adopters and repeat purchasers may respond to different attributes in a different way and firms' response to each sales component, in term of attribute improvements, may be different. The dynamic model in Eq. (4-3a) thus will become $\dot{f}^{w}(t) = \alpha(t) \cdot m\left(A^{w}(t)\right) \cdot \left(1 - f^{w}(t)\right),\ f^{w}(0) = 0$.

Overall sales $s^{w}(t)$ is the sum of the two components of sales, the periodic sales from first-purchase (adoption), $\dot{f}^{w}(t)$, and from repeat purchase $r^{w}(t)$, thus,

$$s^{w}(t) = \dot{f}^{w}(t) + r^{w}(t). \tag{4-4}$$

Following Olson and Choi (1985), repurchases at time *t* that equal disposals are calculated by summing the multiplication of sales in the past by the probability that a product dies at time *t*,

$$r^{w}(t) = \sum_{\tau=0}^{t-1} s^{w}(\tau) \cdot P(t-\tau), \tag{4-5}$$

when $P(\tau)$ is the likelihood that the product is worn out and needs to be replaced after τ time periods in service. Several researchers use different statistic distributions to model the life time distribution $P(\tau)$. Olson and Choi (1985) use a Rayleigh distribution, Kamakura and Balasubramanian (1987) use truncated normal distribution, and Bayus et al. (1989) use Weibull distribution. Lawrence and Lawton (1981) use a simplistic model, where the product lifetime is deterministic, which may be applied to products that expire or need to be disposed of due to regulatory or contract reasons. Kaya et al. (2007) show that not all products are equal and that the lifetime distribution function is product-dependent.

Our model is very similar to previous repurchase models, such as that of Olson and Choi (1985), with the exception that in our model repurchase influences adoption by accelerating attribute improvements, while in previous models adoption is indifferent to repeat purchase. The influence of repeat purchase due to wear-out on adoption rate is a contribution of our method.

To calculate $s^{w}(t)$ at each time *t*, one uses the iteration method as in the first-purchase case adding now the repeat purchase effect $r^{w}(t)$.

4.2.1.2 Repurchase due to Wear-Out when several products coexist in the market

Sometimes there are several coexisting products of the same product category with different attributes in the market. In some cases there are several products in a product line or different brands while in other cases there are several generations that are present in the market at the same time. The markets of all the products together compose the overall market of the category. Since in such cases the products share the same market and often the same technology, each product's attributes impact the attractiveness of all the other products in the category. Technological progress, motivated by overall sales, usually leads to improvements in all products in the product line. However, some products in the product line may improve due to the technological progress more than others. Adopters are influenced by the maximum utility of the product category in their decision whether to adopt, and by the changing relative attractiveness of the various products of the category in their decision about which product to adopt. When repurchase is due to wear-out there is another effect. Adopters of a certain product may reconsider their choice and select another product at the time of repurchase. When the number of units of a certain product disposed of is greater than the sales of the certain product we see a decline in the number of its actual users. The market shares of the products in the product line, as a function of their attributes, can be estimated using a conjoint study.

For modeling a set of *n* products that coexist in the market we extend the scalar functions $f^{w}(t)$, $\dot{f}^{w}(t)$, $r^{w}(t)$ and $s^{w}(t)$ to vectors of length *n*. Note that the market shares of the products in the product line, assuming that customers possess only one product at a time, is divided between several products thus $\sum_{k=1}^{n} f_k^w < 1$ where $f_k^w(t)$ represents the cumulative adoption of product *k*.

The attributes sets $A^{w}(t)$ represents a vector of attributes sets or a matrix of attributes where each row represents the attribute levels set of a certain product.

In addition we use another vector of length *n*:

$B(t)$ = a vector of length *n* of the numbers of actual users (in percentage). While adoption $f_k^w(t)$ represents the number of customers who first adopted product *k*, no matter if they still use it or not, $B_k(t)$ represents the number of customers who really use it. In a case where customers may dispose of a certain product from a product line and switch to another product, $B_k(t)$ may differ from $f_k^w(t)$. Market acceptance $f_k^w(t)$ also does not count customers who first adopted another product and later switched to the product *k*. The number of users, $B_k(t)$, does include customers who first had another product and later switched to product *k*.

The market share of each product depends not only on its attributes set but also on the attributes of the other products. Eqs. (4-1), (4-1a), (4-2), (4-2a) and (4-4) can be directly extended to a vector form. For Eq. (4-3a) we need to replace the remaining market for new adopters $\left(1 - f^{w}(t)\right)$ by the remaining market of users who have never purchased any of the products in the product line, $\left(1 - \sum_{k=1}^{n} f_k^{w}\right)$, thus,

$$\begin{pmatrix} \dot{f}_1^{w}(t) \\ \dot{f}_2^{w}(t) \\ \vdots \\ \dot{f}_n^{w}(t) \end{pmatrix} = \alpha(t) \cdot \begin{pmatrix} m_1\left(A^{w}(t)\right) \\ m_2\left(A^{w}(t)\right) \\ \vdots \\ m_n\left(A^{w}(t)\right) \end{pmatrix} \cdot \left(1 - \sum_{k=1}^{n} f_k^{w}\right) \; ; \quad \begin{pmatrix} \dot{f}_1^{w}(0) \\ \dot{f}_2^{w}(0) \\ \vdots \\ \dot{f}_n^{w}(0) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}. \tag{4-6}$$

When referring to repurchase we assume, for simplicity, that all products have the same lifetime distribution $P(\tau)$. A customer is considered forever an adopter of product *k*, and counted in $f_k^{w}(t)$, once he/she has adopted the product *k* and has not previously purchased any other product of the category. When calculating the number of actual users, $B_k(t)$, which is the number of customers (in percentage) who still possess a certain product and have not disposed of it, we need to consider repurchase effects. Cumulative sales $f_k^{w}(t)$, or market acceptance, is a monotonic non-declining function of time that, when there is a single product *(n=1)*, will finally reach the value 1. When there are several products *(n>1),* each component is a monotonic non-declining function of time and the sum of the components will finally reach the value 1. The installed base, or the number of actual users, $B_k(t)$, is identical to $f_k^{w}(t)$ when there is only one product *(n=1)*, since when a product breaks it is replaced by a new one. However, when there are several products *(n>1)*, customers may dispose of one product (for example product *x*), causing a decline in its installed base $B_x(t)$, and switch to another product (for example product *y*), increasing its installed base, $B_y(t)$, beyond its adoption market share $f_y(t)$.

For example, following the introduction of mobile phones from the analog generation, their adoption increased steadily. When such a phone stopped functioning it was replaced by another phone, probably better, of the same generation (an analog phone). Later, when digital phones appeared, some new adopters still preferred the more established analog phones while others adopted the new digital phones. At that time, when an analog phone stopped functioning customers could choose whether to buy another analog phone or to switch to a digital one. In a timeframe of several years the installed base of analog phones started to decrease, and finally almost vanished, while digital phones (of several generations) became dominant.

The likelihood that a certain product will be repurchased is not the same as the likelihood its being adopted, since the choice is made by a customer who has already adopted. For example, at a certain time the potential market shares of analog phones and digital phones, due to their attributes and market preferences, were 30% and 10%, respectively. For a customer who had already purchased, thus belonging to the 40% potential adopters of either type, and needed to replace a phone, the choice was not whether to adopt but which product to favor. The probability, at that time, that he/she favored an analog phone was 25% (10% out of 40%) and a digital phone 70%.

Starting with no installed base at launch, $B(0) = 0$, we calculate the installed base at the next period by adding the number of units of each specific product adopted, deducting the number of units disposed and adding the number of units repurchased. Since the total number of repurchases, of all products, is the sum of the units disposed of all *n* types $\sum_{k=1}^{n} r_k^w(t)$, we know how many customers need to make a repurchase choice. The likelihood of choosing a certain product *k*, given that this customer has adopted before, is the market share of this product type $m_k\left(A^w(t)\right)$ divided by the sum of the market shares of products of all *n* types $\sum_{k=1}^{n} m_k\left(A^w(t)\right)$; thus, for every product k in the product line,

$$\underbrace{B_k(t+1)}_{\substack{next\\ actual\\ users}} = \underbrace{B_k(t)}_{\substack{present\\ actual\\ users}} + \underbrace{\dot{f}_k^w(t)}_{\substack{new\\ adoption}} - \underbrace{r_k^w(t)}_{disposals} + \underbrace{\underbrace{\sum_{i=1}^{n} r_i^w(t)}_{\substack{total\_number\_of\\ customers\_who\\ repurchase}} \cdot \underbrace{\frac{m_k\left(A^w(t)\right)}{\sum_{i=1}^{n} m_i\left(A^w(t)\right)}}_{\substack{The\_probability\\ to\_choose\_product\_k}}}_{replacements} . \tag{4-7}$$

The numbers of actual users of product *k*, at next period, *t+1*, $B_k(t+1)$ equals the sum of the number of actual users at time *t*, $B_k(t)$ and the change in the installed base. The change is composed of new adopters of product *k*, $\dot{f}_k^w(t)$, deducting disposals (or the number of products of type *k* that broke) during period *t*, $r_k^w(t)$, and adding replacements. The replacements are calculated as the total number of repurchases $\sum_{k=1}^{n} r_k^w(t)$ multiplied by the drive to choose product k, $m_k\left(A^w(t)\right)$, normalized by the overall market share of all products in the line $\sum_{k=1}^{n} m_k\left(A^w(t)\right)$.

When for a certain product *k* the new purchases, due to adoption and repeat purchase, are less than disposals, we will see a decline in the installed base $B_k(t)$. When there is only a single product *(n=1)* the installed base $B(t)$ at Eq. (4-7) is identical to $f^w(t)$ since disposals and replacement are identical. When there are several coexisting products *(n>1)* there may be a decline in the installed base of some and an increase in the installed base of others. A decline in the installed base, described by Rogers (1962), is not modeled by other diffusion models.

The contribution of this model, relative to previous diffusion models that include repurchase due to wear-out, is that it describes not only the overall adoption and repurchase volumes but also the switch between products of the same category. Modeling the transitions between the products is based on the decision, at adoption and repurchase time, which is influenced by the attributes of the products. We demonstrate the implementation of the model for the hybrid car case in chapter 6.

4.2.2 Repurchase due to Upgrade

Bayus (1988) explained that for many products repeat purchase occurs due to a difference between the utility of an owned product and that of products available on the market, and not due to wear-out of the old product. For simplicity's sake, we assume such a product's lifetime is long and repeat purchase due to wear-out can be ignored. Another assumption we take for the sake of simplicity is that there is a market consensus of the relative importance of attributes, and the market is homogenous in its attribute preferences, so we can refer to the scalar utility of the product, at the market level, rather than to the vector of attributes levels, and use Eqs. (4-1b), (4-2b) and (4-2c) for adoption. Since the market is homogenous we refer to a single product and not to a product line. As in the case of repurchase due to wear-out, we forecast sales as a sum of adoption and repurchase when adoption and repurchase are influenced by the product's utility. The utility improvements, motivated by sales, are influenced, as for the case of repurchase due to wear-out, by both adoption and repurchase, the difference being that repurchase is not a function of the product's lifetime, since the old products still function, but due to a desire to upgrade to a better product. We model this phenomenon and its effect on diffusion.

We will use the following notations for the case of a single product:

$f^u(t)$ = the cumulative market acceptance (in percentage) at time *t*, that stems from adoption, when there is repurchase due to upgrade.

$r^u(t)$ = the periodic repurchase sales (in percentage) that stem from a product ceasing to function (wearing out) and needing to be replaced.

$s^u(t)$ = the periodic overall sales (in percentage) at time *t*, that stem from either adoption or repeat purchase due to wear-out.

t_p = the time of previous purchase for a certain group of customers.

$\alpha_{t_p}(t)$ = the number (in percentage) of customers who previously purchased at t_p and consider an upgrade at *t*.

$r_{t_p}(t)$ = the number (in percentage) of customers who previously purchased at t_p and upgraded at *t*.

$u^u(t)$ = product's utility at time *t* influenced by sales the stem from both adoption and repurchase due to upgrade or technological obsolescence.

Similarly to Eq. (4-1b), potential adoption level (in percentages) of the product with utility $u^u(t)$, is $m(u^u(t))$. Also, given that an acquisition is considered, $m(u^u(t))$ represents the likelihood that consumers will choose to adopt the new product with utility $u^u(t)$ from among the alternatives, which also include buying old technology or not buying at all, given that a purchase is considered. As in the case of adoption, when the purchase consideration rate is $\alpha(t)$, the probability density of actually adopting the product with utility $u^u(t)$, will be $\alpha(t)\cdot m(u^u(t))$.

In the presence of repurchase, firms are influenced, in their product improvement activities, not only by adoption $f^u(t)$ but also by the sales volumes that stem from repeat purchase $r^u(t)$. Thus, $u^u(t) = u\left(A(f^u(t), r^u(t))\right) = u(f^u(t), r^u(t))$. The dynamic model in Eq. (4-3b) will thus become $\dot{f}^u(t) = \alpha(t)\cdot m(u^u(t))\cdot(1 - f^u(t))$, $f^u(0) = 0$.

Overall sales, $s^u(t)$, as in the case of repurchase due to wear-out, see Eq. (4-4), is the sum the two components of sales, adoption $\dot{f}^u(t)$ and repeat purchase $r^u(t)$, and thus,

$$s^u(t) = \dot{f}^u(t) + r^u(t) \quad . \tag{4-8}$$

For upgrades, or repurchase due to obsolescence, we cannot rely on product lifetime, since an upgrade occurs when the old product is still functional. Following Bayus (1988), the drive to upgrade is the difference in the utility that a customer receives from his/her owned product and the utility that more advanced products, which became available later, can provide. The utility progress may not be constant, but may follow market growth rates, so the rate of upgrading may vary as well. At times of rapid technological (and utility) progress, upgrades speed up. When technology evolution slows, upgrading slows as well. Since the motivation for an upgrade is the perceived utility difference between the owned product and products available in the market, we assume that the probability *P*, that customers who previously purchased at t_p will upgrade at t, as a function of the perceived utility difference between the products. Thus,

$$P = P_u\left(u^u(t) - u^u(t_p)\right) = P(\Delta u)\,;\; t_p \le t \;, \tag{4-9}$$

when $u^u(t_p)$, $u^u(t)$ are the utilities at t_p, t, respectively and Δu is the utility difference between them. The probability function describes the diversity in the population. Some customers are motivated by small improvements while others upgrade only when improvements are more significant. Note that Eq. (4-9) incorporates an assumption that customers, on average, maintain the same utility difference as a motive for upgrade. We expect that at $t = t_p$ the probability for upgrade equals zero since there is no utility improvement. The specific probability function $P(\Delta u)$ needs to be assessed based on empiric data. We demonstrate how this specific probability is estimated for the digital camera case in chapter 7.

To estimate how many customers who purchased at t_p would upgrade at t, denoted as $r_{t_p}(t)$, we multiply the number of customers who consider upgrading $\alpha_{t_p}(t)$ by the probability that they upgrade. Thus,

$$r_{t_p}(t) = \alpha_{t_p}(t) \cdot P_u\left(u^u(t) - u^u(t_p)\right)\,;\; t_p < t \;. \tag{4-10}$$

Eq. (4-10) is aligned with Bayus' (1988) results, that increasing utility progress rate accelerates repurchase. When $t = t_p$, repurchase at the time of purchase $r_{t_t}(t_p)$ equals zero since there is no utility improvement.

We assume that the relevant population that is contemplating an upgrade includes anybody who has purchased in the previous periods. For estimating how many customers previously purchased at t_p and consider repurchase at t, denoted $\alpha_{t_p}(t)$, we take the sales at t_p, $s^u(t_p)$, and deduct those who have already upgraded. Thus,

$$\alpha_{t_p}(t) = s^u(t_p) - \sum_{\tau=t_1}^{t-1} r_{t_p}(\tau)\,;\; t_p < t \;. \tag{4-11}$$

When $t = t_p$ the number of customers who still possess a product with utility $u^u(t_p)$ equals the sales at t_p, $s^u(t_p)$. This number declines with time since some of these customers upgrade to newer products.

To calculate repurchase $r^u(t)$, we sum the repurchase that stems from previous periods, similarly to Eq. (4-5), following the concept outlined by Olson and Choi (1985). To calculate repurchase that stems from a certain period, we multiply the likelihood of upgrading by the relevant population, see Eq. (4-10), and sum the repurchase originated from each past period similarly to Eq. (4-5), following Olson and Choi (1985).

To calculate overall repurchase, $r^u(t)$, of all segments, which is the number of customers (in percentage) who repurchase at *t*, due to technological obsolescence, we sum the numbers of all customers who purchased before time *t* and upgraded at time *t*.

$$r^u(t) = \sum_{k=0}^{t-1} r_k(t) \ . \tag{4-12}$$

As opposed to Olson and Choi (1985), who relate the repeat purchase decision to an external event (i.e., product end of life), at repurchase due to obsolescence, we relate the repeat purchase decision to an internal drive to upgrade. While the probability function at Eq. (4-5) describes the distribution of products' lifetime, the probability function at Eq. (4-9) describes the variety in the population. Some customers upgrade when there are small utility improvements, relative to the product they possess, and some customers upgrade when the utility improvement is more significant.

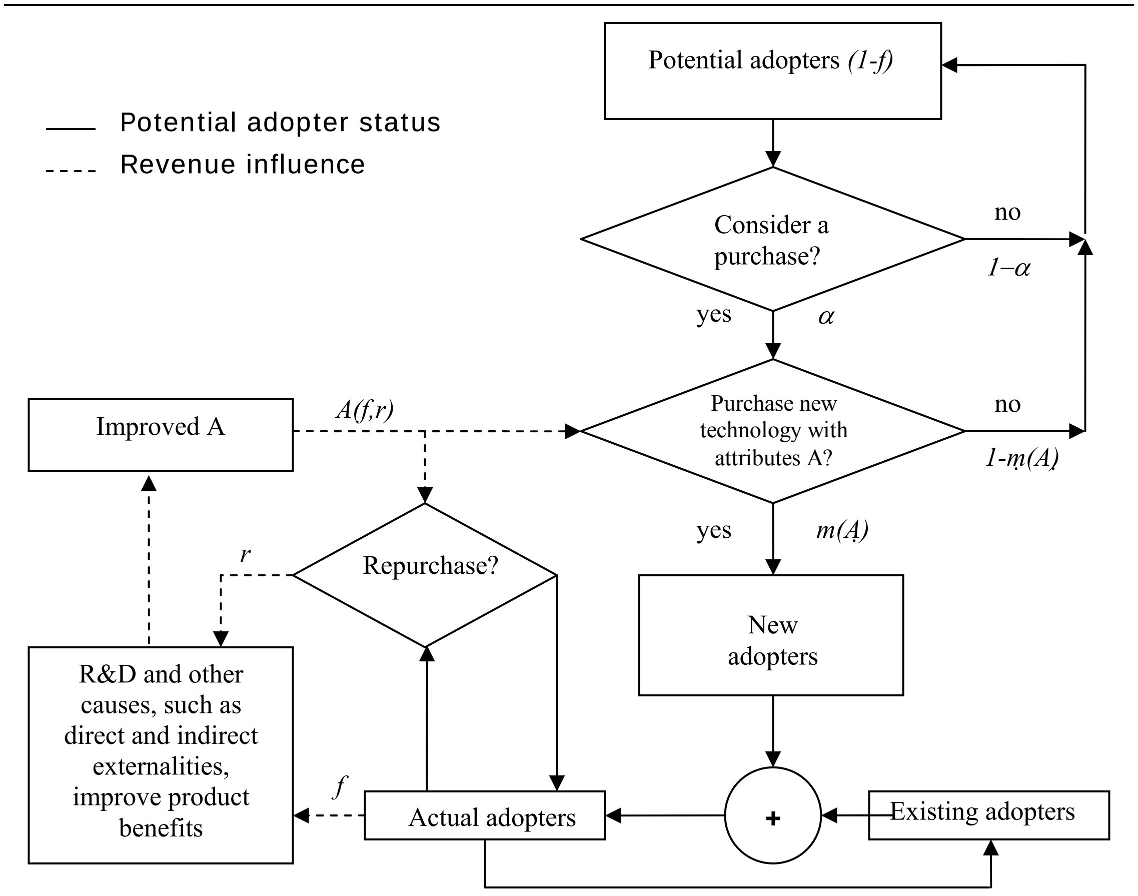
While obsolescence is mentioned in previous literature (see Bayus 1988; Steffens 2002, Kaya et al. 2007) as a drive to repurchase, and as proven by Mont (2008), obsolescence is a dominant factor for driving repurchase for many products, the models proposed for forecasting it are based on time. The issue of the mismatch between the drive explanation, which is utility improvement and modeling based on time, is mentioned by Bayus (1991). He notes that for forecasting a time-based model might fit. Bayus (1991) analyzed the impact of product improvements on repeat purchases but did not incorporate it in a model and did not use it for forecasting. Our contribution is in that we incorporate the path of utility improvement and its influence, on sales in general and on repeat purchase due to obsolescence in particular, in a diffusion model which can be used for forecasting. In addition to forecasting adoption and repurchase, the proposed method can model and explain effects such as the extension of upgrading time described by Gordon (2006).

The model presented here, which includes repeat purchase impact, integrates the customer's decision process as adopters (Eqs. (4-1), (4-1a) and (4-1b)), their repurchase considerations (Eqs. (4-5), (4-9), (4-10) and (4-11)), market dynamics (Eqs. (4-3), (4-3a), (4-3b), (4-4), (4-6), (4-7), (4-8) and

(4-12)) and the firm's and service providers' response (Eq. (4-2)). The interdependency between these functions requires that they be estimated simultaneously. Based on initial product attributes we can assess sales and then the attributes' progress that stems from these sales. Customers and firms' decisions flows, based on Figure 4 but including repeat purchase effect, are presented in Figure 5.

In addition to the adoption part, which is the same as Figure 4 explained above, actual adopters who repurchase remain adopters. This remains valid until a new attractive alternative technology causes customer attrition. Until a new technology, and a new product category, is introduced the transition to repurchase state does not change market adoption status. This is denoted in Figure 5 by solid lines between actual adopters and repurchase. The influences of attributes on repurchase decision due to obsolescence and of repurchase on attributes are denoted in Figure 5 by a broken line. Adopters may decide to repurchase due to wear-out or due to improved attributes which make their owned product obsolete. Adopting or upgrading a product creates a cash flow on the supplier's side. Some of the revenues are directed to R&D, which improves the product and makes it a more attractive alternative when potential adopters consider a purchase and when adopters consider a repurchase.

Figure 5: Customer Purchase Decision and Firms and Service Providers Flow



In the following chapter, we discuss some insights that stems from our method and describe some of its implications. We demonstrate how a variety of phenomena and diffusion curves can be modeled by using the model with speculated parameters. Next, we explain how one can actually estimate the parameters of the model's functions for actual cases. For the hybrid car case we use the model with few attributes, referring to a product line and market segments, for adoption and repurchase due to wear-out. We assess the parameters of the functions $\alpha(t)$, $m(A)$ and $A(f)$ for adoption and of the functions $P(\tau)$ and $r^{w}(t)$ for repeat purchase. We forecast developments in the hybrid car market and generations substitution, and perform a sensitivity analysis of the forecast to the estimated parameters. For the digital camera case we use the model with a richer set of attributes, referring to product utility in a homogenous market, for adoption and repurchase due to upgrade. We assess the parameters of the functions $\alpha(t)$, $u(A)$, $m(u(A))$ and $u(f)$ for adoption and of the functions $P(\Delta u)$ and $r^{u}(t)$ for repeat purchase. We benchmark our digital camera market forecast against actual sales and other models.

5. Illustrative Examples of the Attributes-Based Dynamic Model

In this chapter we describe how various phenomena, described in previous literature and explained in different ways, are modeled using our method.

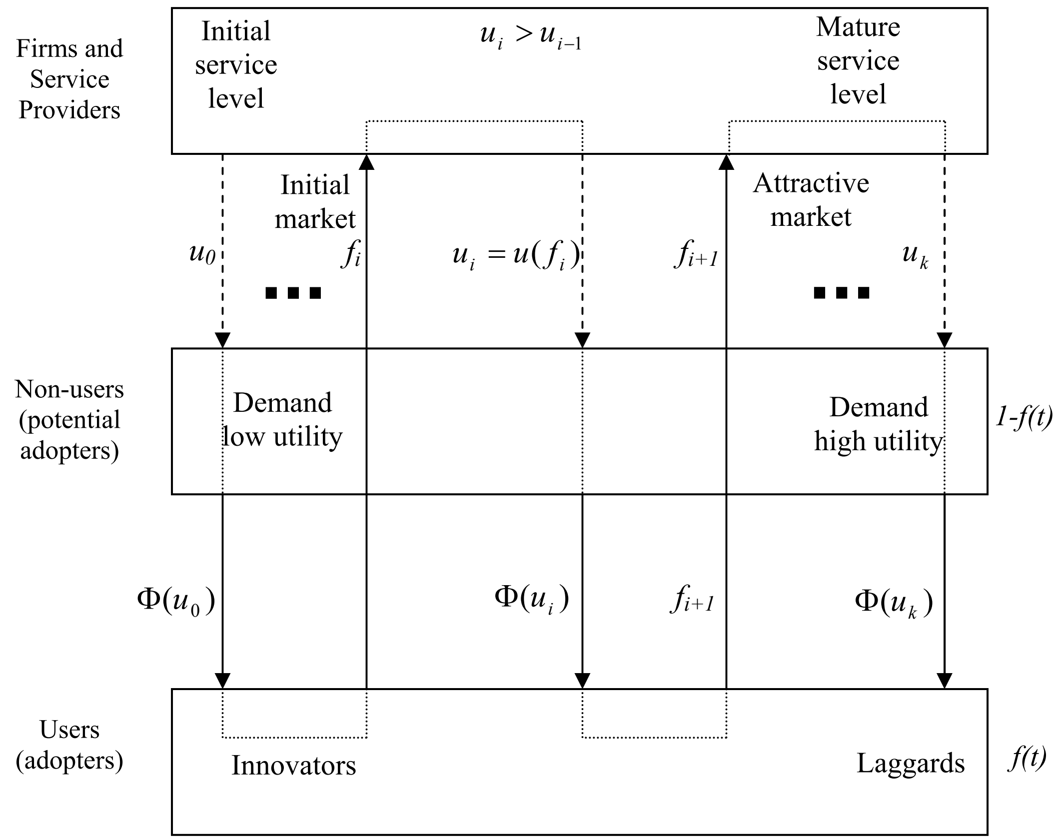
5.1 Additional Insights - Product Adopters' Profiles

The attributes-based diffusion model can be used to shed new light on the profiles of product adopters. For simplicity's sake, we discuss this insight under the assumption of market homogeneity in attribute preferences and refer to (2b). As it appears in our model, early adopters (innovators of the Bass model) are driven by acute needs to purchase the product even when it has a low utility level and a high price. Thus, they are influenced not by mass media, which is a low involvement medium, but primarily by internal specific needs. The need-based reasoning explains why innovators are product-specific. In our model, late adopters (imitators of the Bass model) are consumers who are satisfied with the current alternatives. They will adopt the product only when it improves to provide more benefits than the currently existing alternatives. The new product has to compete not only with the existing technological attributes, but usually also with a well-deployed infrastructure (indirect externalities) that supports the well-established[13] technology. Late adopters or laggards, as explained by Goldenberg and Oreg (2007), are sometimes those who are heavily invested in the old technology. Goldenberg and Oreg (2007) present the example of those who had a large library of vinyl records or audio cassettes and were not enthusiastic about switching over to CDs. The benefits of better sound and a compact package were nullified by the need to re-purchase a new inventory of music records. The same is true for professional photographers and photography hobbyists who had their own dark room, developing equipment, lenses and other paraphernalia for film photography and development, all of which became obsolete with the invention of the digital camera. We expect taxi drivers to be innovative and early adopters of hybrids due to their acute need for fuel-efficient cars. However, we expect them to be late adopters or laggards for plug-in hybrids, since such hybrids need to recharge their batteries for several hours in order to take advantage of the plug-in feature. Such a recharge pattern is fine for commuters who usually park their cars for several hours after driving to and from work. Characterizing adopters according to the match of product benefits to their need enables marketers to identify them and improves firms' capability to plan efficient promotion strategies.

In our model, knowledge about the product (which is a precondition for considering a purchase) spreads through WOM, media and Internet, as shown by Midgley (1976), at a faster rate than adoption. The knowledge of the product and its benefits is available to potential adopters before the product's utility reaches the level of their demands. The limiting factor of adoption is not knowledge of the product but its match to customer needs. We describe the process of adoption and utility mutual influence and simultaneous growth in Figure 6.

[13] Proven performance of the existing technology, versus uncertainty of the new one, can be perceived as a type of direct externality.

Figure 6: The Utility-Based Dynamic Model



5.2 Prediction of Abnormalities in Diffusion

Moore (1991) discusses a decline in sales that for many products occurs during the period of rapid growth. This phenomenon was ignored by earlier researchers[14] and was considered a random interference. Moore (1991) indicates that such a phenomenon, which he called a 'chasm', exists for many products, resulting in diverse managerial implications. Understanding the chasm may avoid investors' disappointment and encourage the required patience that is necessary for "crossing the chasm". Moore (1991) explains that there is a distinction between early adopters that have certain needs and the early majority that is more conservative. In order to cross the chasm, firms have to adjust their products to the requirements of the early majority. Goldenberg et al. (2002) prove that a "saddle", which is a decline in sales during market growth, may occur at the transition between generations if introduction timing is not optimal. Our model can model the chasm phenomenon, as well as other "abnormalities". To be more specific, we next present some illustrative examples of the

[14] Bass' (1969) data show a chasm but he focuses on the major trend.

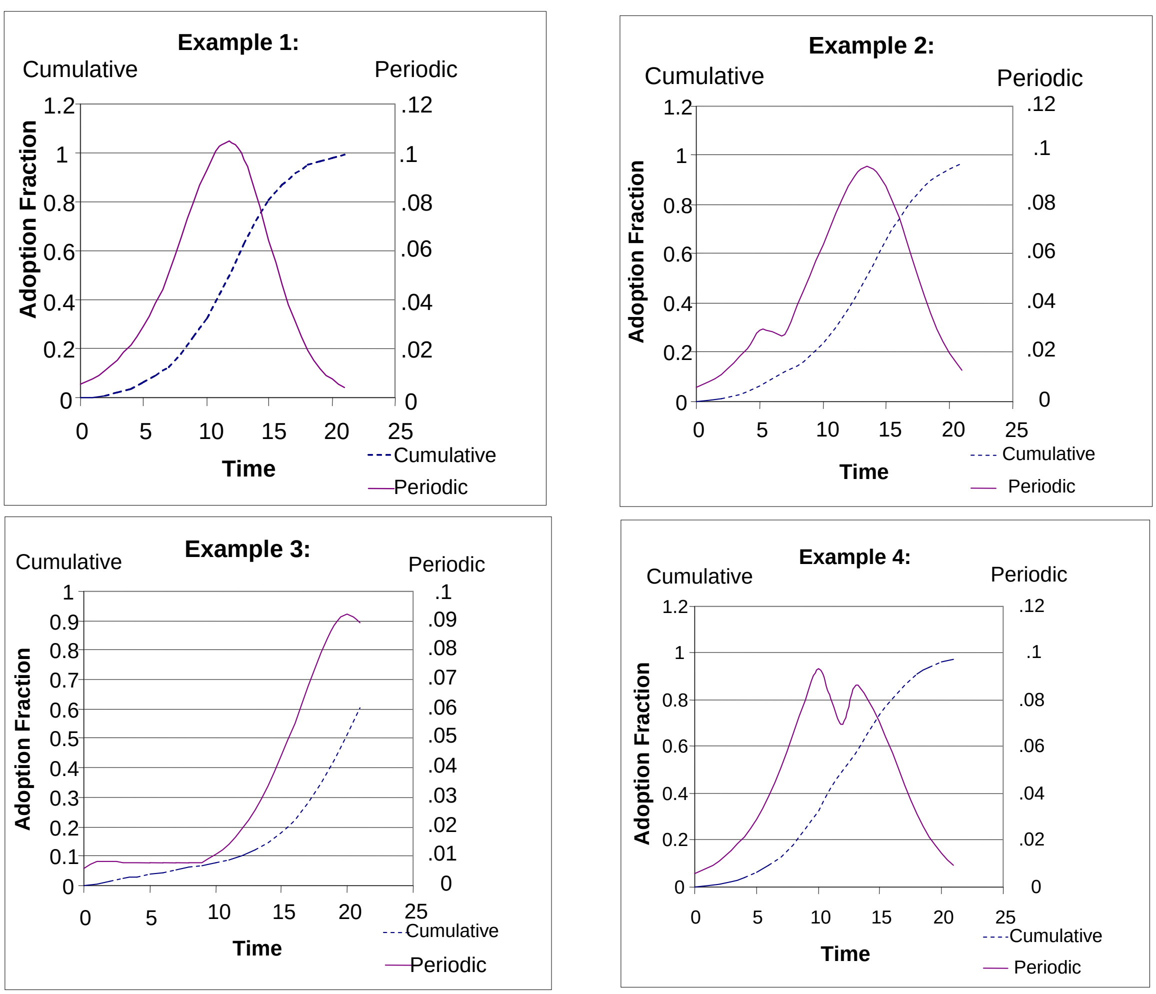
case of a market with homogenous attributes evaluation, where we can refer to the utility at the aggregated level, where *u(f)* (see Eq. (4-2b)) is linear to adoption level i.e., $u(f) = u_0 + bf$. Our assumption is that the product's utility is u_0 when the product is introduced to the market and its utility improves by b percentage points, due to externalities or product improvements, for every 1% market growth.

Example 1. Consider that $\Phi(u)$, see Eq. (4-2c), is also linear, i.e., $\Phi(u) = \Phi_0 + \beta \cdot u$. The increase in the purchase driving force is proportional to the increase in utility with the factor β. At launch, when $u = u_0$, the purchase driving force $\Phi(u_0) = \Phi_0 + \beta \cdot u_0$ equals the sales volume for the first period. Consider the following values for our parameters,

$$(u_0, \quad b, \quad \Phi_0, \quad \beta) = (1.053, 0.64, -0.76, 0.728). \qquad (5\text{-}1a)$$

The diffusion curves, for both cumulative and periodical sales, which are identical to the "classic" diffusion curves, are shown in Figure 7.

Figure 7: Possible Marketing Phenomena Explained by the Utility-Based Model



Example 2. Now we consider that the driving force $\Phi(u)$ has the following non-linear form,

$$\Phi(u)=\begin{cases} u_0+\beta u & u<1.1 \\ u_0+1.1\beta & 1.1\le u<1.16, \\ u_0+(u-0.06)\beta & 1.16\le u \end{cases} \tag{5-1b}$$

with $(u_0,\ b,\ \Phi_0,\ \beta)$ as in Eq. (5-1a). According to Eq. (5-1b), the attractiveness of the product or the purchase driving force does not grow for all utility values *u,* but remains the same for a certain utility range. In this case, the periodical sales curve shows a chasm. The decline in sales can be explained by the purchase driving force function $\Phi(u)$, which is constant for $1.1\le u\le 1.16$. This means that although the utility *u* increases, the number of potential customers that are interested in the product in this utility range, and represented by $\Phi(u)$, does not increase. Note that sales are a multiplication of $\Phi(u)$ by *(1-f),* which represents the saturation effect. Saturation causes sales to decline when $\Phi(u)$ is constant. When $\Phi(u)$ increases again (for *u>1.16*), the saturation effect is compensated by the growing potential market, represented by $\Phi(u)$, and sales rise. This rise is described by Moore (1991) as "crossing the chasm."

Example 3. Now we deviate from the previous example by considering:

$$\Phi(u)=\begin{cases} u_0+\beta u & u<1.06 \\ u_0+1.06\beta & 1.06\le u<1.12\cdot \\ u_0+(u-0.06)\beta & 1.12\le u \end{cases} \tag{5-1c}$$

The deviation means that the slowdown in product attractiveness or the purchase driving force occurs for a lower utility (1.06 rather than 1.1) and happens a little earlier. Again we use $(u_0,\ b,\ \Phi_0,\ \beta)$ as in Eq. (5-1a). Following Figure 7, the periodical sales show that for a long time the sales volumes are small until they rapidly take off. The impact on sales is that the product has a long runway before take-off. It might be interesting to see if *Example 3* can explain the behavior of a product like HDTV, which has not yet taken off.

Example 4. Now we consider another deviation of $\Phi(u)$ (with a slowdown at a later stage):

$$\Phi(u)=\begin{cases} u_0+\beta u & u<1.27 \\ u_0+1.27\beta & 1.27\le u<1.33, \\ u_0+(u-0.06)\beta & 1.33\le u \end{cases} \tag{5-1d}$$

using $(u_0,\ b,\ \Phi_0,\ \beta)$ as in Eq. (5-1a). We maintain that the periodical sales curve shows a double-hump curve (decline and revival) (see Figure 7).

Similar effects happen when the driving force is linear, but the firms fail to increase the utility at a constant rate. We demonstrated the effects of a slight distortion in a linear dependency.

Other forms of diffusion can be explained by different *u(f)* and $\Phi(u)$ functions. Note that similar effects to those presented in Figure 7 are explained by Van den Bulte and Joshi (2007) in a different way.

5.3 Generations Substitution

When we refer to generations substitution, *u(f)* is not linear but progresses in steps. While gradual improvements can be represented by a linear relation between market f and utility u, i.e., $u\left(f(t)\right) = u_0 + b \cdot f(t)$, a generation substitution can be represented by a stepwise function, i.e., $u\left(f(t)\right) = u_0 + b \cdot f(T \cdot \left\lfloor \frac{t}{T} \right\rfloor)$, where T is the time between generations (which for simplicity is assumed to be the same between all successive generations) and $\left\lfloor \frac{t}{T} \right\rfloor$ is the integer of the rational number $\frac{t}{T}$. We demonstrate how the diffusion curve is influenced by changes in the time between generations. We assume that $\Phi(u)$ is also linear, i.e., $\Phi(u) = u_0 + \beta \cdot u$.

Example 5. We assume that the time T between generations is 2, which means that a new generation is launched every 2 periods.

$$\left(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad T\right) = (1.053, 0.64, -0.76, 0.728, 2). \tag{5-2a}$$

The diffusion curves, for both cumulative and periodic sales, are shown in *Example 5* in Figure 8.

Example 6. We assume that the time T between generations is 3, which means that a new generation is launched every 3 periods.

$$\left(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad T\right) = (1.053, 0.64, -0.76, 0.728, 3). \tag{5-2b}$$

The diffusion curves, for both cumulative and periodic sales, are shown in *Example 6* in Figure 8.

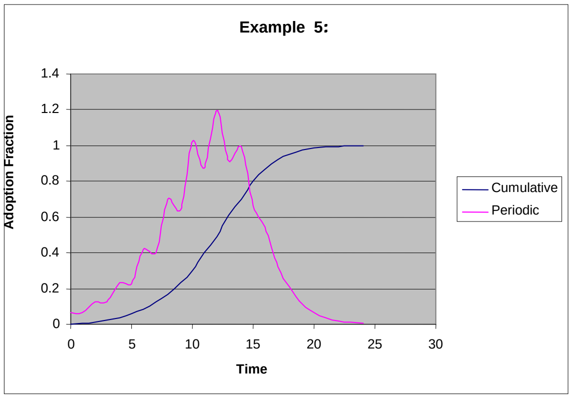
Example 7. We assume that the time T between generations is 4, which means that a new generation is launched every 4 periods.

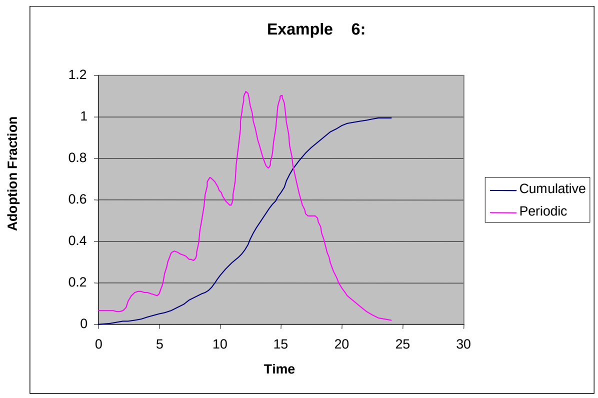
$$\left(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad T\right) = (1.053, 0.64, -0.76, 0.728, 4). \tag{5-2c}$$

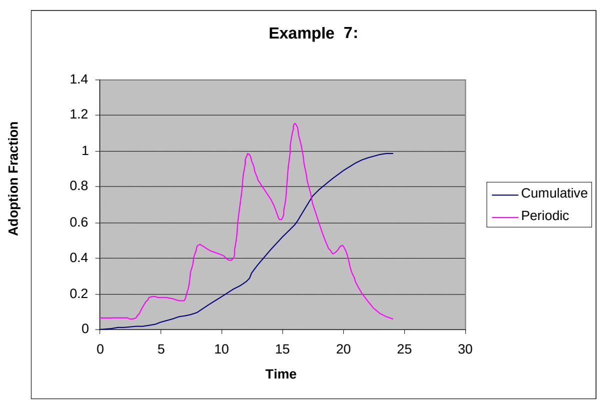
The diffusion curves, for both cumulative and periodic sales, are shown in *Example 7* in Figure 8.

The examples given above demonstrate that generations substitution curves can be described in our model with an elegant model and 5 parameters.

Figure 8: Diffusion with Generations Substitution







5.4 Repeat Purchase Due to Physical Wear-Out

The durability assumption, used in the Bass model, is often unrealistic. Products need to be replaced after some time in service. This time *T* may be fixed, as some products are replaced in a pre-determined time, but the usual case is that the product lifetime is statistically distributed, typically with some statistic distribution, with some mean *T*. Repurchase, see Eq. (4-5), depends on the nature of the product's lifetime distribution. In prior research (see Olson and Choi 1985; Steffan 2002), repurchase causes an increase of sales volumes, see Eq. (4-4), but does not influence adoption. In our model, since attribute improvements are motivated and financed by sales, product evolution is driven by repeat purchase as well. This evolution might influence non adopters to adopt, thus increasing adoption as well. For some products, such as mobile phones, where users are registered, firms may have the information of adoption and repurchase separately. For other products firms have the information of overall sales but cannot distinguish between new adopters and repeat purchasers. In cases when firms can assess adoption and repeat purchase separately they may respond differently, in terms of which attributes to improve, to each sales source. In other cases firms simply respond to overall sales. We demonstrate repeat purchase impact, using the preference homogeneity assumption, which enables us to refer to utility rather than to each specific attribute, assuming a linear relation between overall sales and utility. The expected utility as a function of cumulative sales *S* is:

$$u(S) = u_0 + b \cdot S \quad . \tag{5-3}$$

The cumulative sales $S(t) = \int_0^t s(\tau) d\tau$ are calculated using Eq. (4-4) as the integration in time of sum of periodic adoption and repurchase, or in the discrete form, $S(t) = \sum_{\tau=0}^{t-1} s(\tau)$. As in *Example 5* of the previous case above (with no repurchase) we consider that $\Phi(u)$ is also linear, i.e., $\Phi(u) = \Phi_0 + \beta \cdot u$. We demonstrate, using several examples, how the function of product lifetime distribution, $P(\tau)$, influences repurchase, see Eq. (5-5), and indirectly through the influence on attributes, also adoption.

The simplest form of product lifetime distribution, $P(\tau)$, which characterizes products with a regulated lifetime, is:

$$P(\tau) = \begin{cases} 1 & \tau = T \\ 0 & otherwise \end{cases} \quad . \tag{5-4}$$

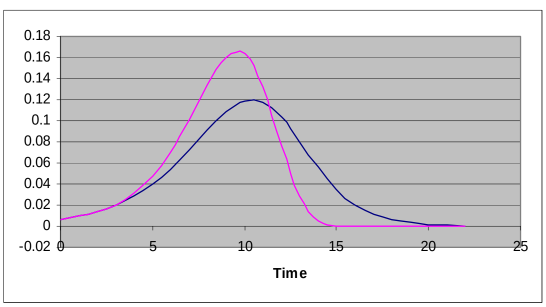
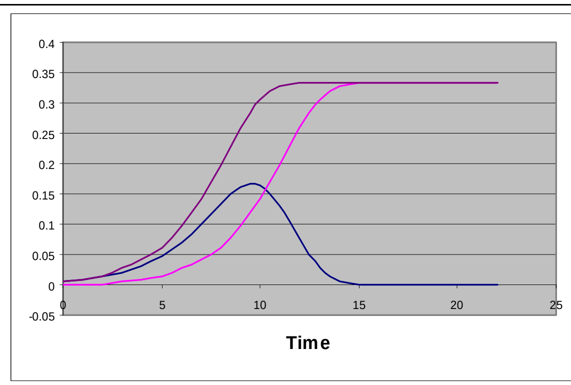
Such a product lifetime distribution characterizes products such as licensed software, which expires after a pre-determined time *T*, or products that must be replaced after some time in service due to a contract or regulatory requirements. With product lifetime distribution, $P(\tau)$, as Eq. (5-4), repurchase is calculated, based on Eq. (4-5) as:

$$r^w(t) = \begin{cases} s^w(t-T) & t \geq T \\ 0 & otherwise \end{cases} . \tag{5-5}$$

We see the effect of different values of *T* by keeping the value of all other parameters of the model, $(u_0, \quad b, \quad \Phi_0, \quad \beta)$, the same for all the examples while only the parameter *T* varies. We present the periodic adoption curves, with and without repurchase effect, and also the components of sales (adoption and repurchase) for each example.

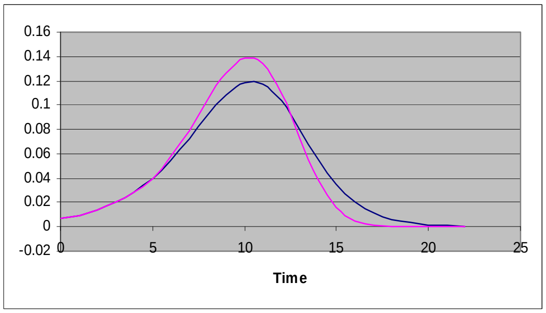
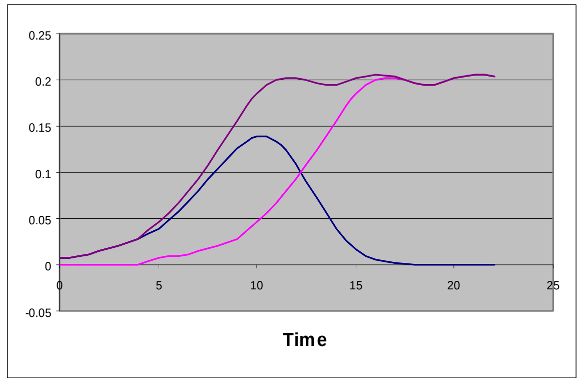
Example 8: T=3.

$$(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad T) = (1.053,\ 0.64,\ -0.76,\ 0.728,\ 3). \tag{5-6a}$$

A comparison between adoption with and without the influence of repurchase	Adoption $\dot{f}^w(t)$ / Repurchase $r^w(t)$ / Sales $s^w(t)$
	
Repurchase No Repurchase	Adoption Repurchase Sales

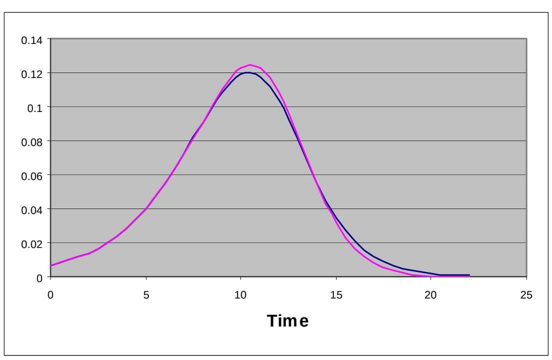
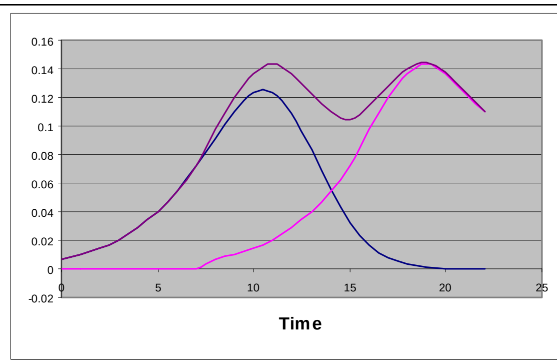
Example 9: T=5.

$$\left(u_0,\quad b,\quad \Phi_0,\quad \beta,\quad T\right)=(1.053,\ 0.64,\ -0.76,\ 0.728,\ 5). \tag{5-6b}$$

<table>
<tr><td>A comparison between adoption with and without the influence of repurchase</td><td>Adoption $\dot{f}^{w}(t)$ / Repurchase $r^{w}(t)$ / Sales $s^{w}(t)$</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Repurchase
No Repurchase</td><td>Adoption
Repurchase
Sales</td></tr>
</table>

Example 10: T=8 .

$$\left(u_0,\quad b,\quad \Phi_0,\quad \beta,\quad T\right)=(1.053,\ 0.64,\ -0.76,\ 0.728,\ 8). \tag{5-6c}$$

<table>
<tr><td>A comparison between adoption with and without the influence of repurchase</td><td>Adoption $\dot{f}^{w}(t)$ / Repurchase $r^{w}(t)$ / Sales $s^{w}(t)$</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Repurchase
No Repurchase</td><td>Adoption
Repurchase
Sales</td></tr>
</table>

As expected, and as seen from the examples above, as a product's lifetime shortens, and replacement becomes more frequent (lower *T*), the impact on adoption intensifies. When *T=8* the adoption curve is almost the same as adoption without repurchase. When *T=3* the influence of repurchase on adoption is significant and the adoption curve is very different from adoption without the repurchase effect. Another phenomenon that we notice in the examples is that long product lifetime *T* may create high amplitude oscillations of sales volume. The frequency of the oscillations is *1/T*.

A more common case is when the product lifetime is not deterministic, but has some distribution, $P(\tau)$. The Rayleigh distribution was chosen by Olson and Choi (1985) and other researchers to describe a product's lifetime. It describes a product that will very likely survive for approximately its lifetime, but there is some probability of it lasting for a shorter time. There is also a small probability, which drops fast as lifetime extends, that it will survive much longer. When lifetime has Rayleigh distribution (probability density is $f(t) = \frac{t}{\sigma^2} e^{-\frac{t^2}{\sigma^2}}; t \geq 0$), the probability that the product will survive to time τ, or will have a lifetime between $\tau - 1$ and τ, is:

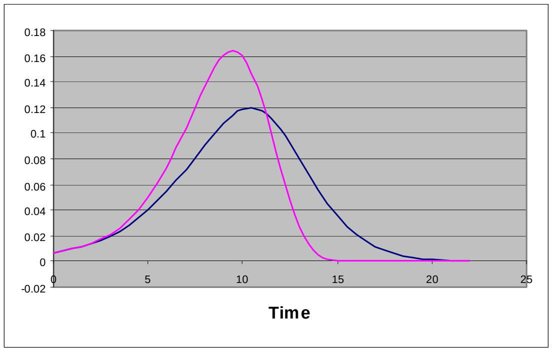
$$P(\tau) = e^{-\frac{(\tau-1)^2}{2\sigma^2}} - e^{-\frac{\tau^2}{2\sigma^2}};\ \tau > 0. \tag{5-7}$$

The expectancy of the Rayleigh distribution, or the average lifetime of a product, is $E(\tau) = \sigma \cdot \sqrt{\frac{\pi}{2}}$.

We present the impact of repurchase due to wear-out on adoption and repurchase, when product lifetime is described by a Rayleigh distribution, The repurchase and sales are calculated using Eqs. (4-5) and (4-4). We use several values of product average lifetime as shown in the following examples:

Example 11: $E(T) = 3 \Rightarrow \sigma = 2.39$.

$(u_0,\quad b,\quad \Phi_0,\quad \beta,\quad \sigma)$ =(1.053, 0.64, -0.76, 0.728, 2.39). (5-8a)

<table>
<tr><td>A comparison between adoption with and without the influence of repurchase</td><td>Adoption $\dot{f}^{w}(t)$ / Repurchase $r^{w}(t)$ / Sales $s^{w}(t)$</td></tr>
<tr><td>


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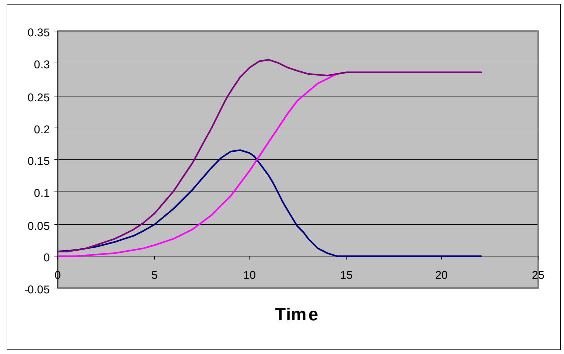
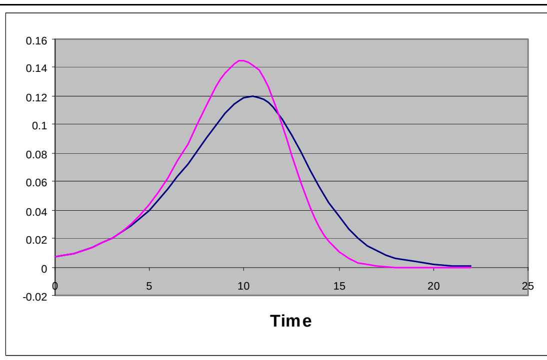


</td></tr>
<tr><td>Repurchase
No Repurchase</td><td>Adoption
Repurchase
Sales</td></tr>
</table>

Example 12: $E(T) = 5 \Rightarrow \sigma = 3.99$.

$(u_0,\quad b,\quad \Phi_0,\quad \beta,\quad \sigma)$=(1.053, 0.64, -0.76, 0.728, 3.99). (5-8b)

<table>
<tr><td>A comparison between adoption with and without the influence of repurchase</td><td>Adoption $\dot{f}^{w}(t)$ / Repurchase $r^{w}(t)$ / Sales $s^{w}(t)$</td></tr>
<tr><td>


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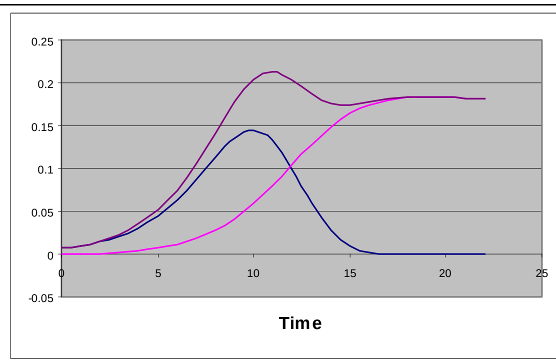
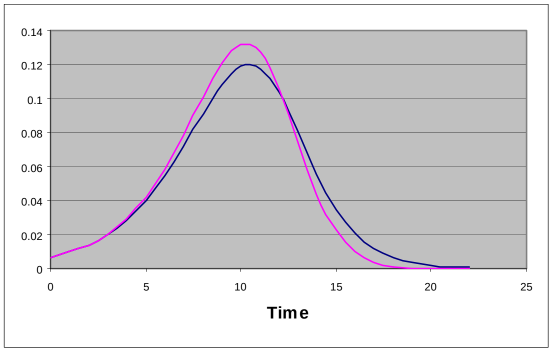


</td></tr>
<tr><td>Repurchase
No Repurchase</td><td>Adoption
Repurchase
Sales</td></tr>
</table>

Example 13: $E(T) = 8 \Rightarrow \sigma = 6.38$.

$$(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad \sigma) = (1.053,\ 0.64,\ -0.76,\ 0.728,\ 6.38). \tag{5-8c}$$

<table>
<tr><td>A comparison between adoption with and without the influence of repurchase</td><td>Adoption $\dot{f}^w(t)$ / Repurchase $r^w(t)$ / Sales $s^w(t)$</td></tr>
<tr><td>


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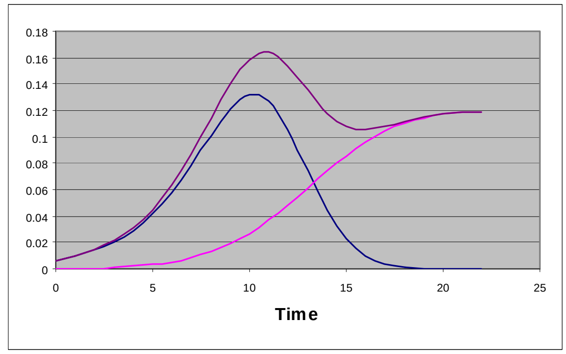


</td></tr>
<tr><td>Repurchase
No Repurchase</td><td>Adoption
Repurchase
Sales</td></tr>
</table>

The effect of a statistically distributed lifetime, versus a fixed lifetime, as reflected in a comparison of (Eqs. 5-7a,b,c) and (Eqs. 5-8a,b,c), is that when the lifetime is not fixed but statistically distributed, the oscillations are dampened. Indeed in mature markets, where repurchase due to wear-out is dominant, sales are usually stable and do not oscillate.

5.5 Repeat Purchase Due to Obsolescence

Repeat purchase due to obsolescence, when customers upgrade the products they own not because they no longer function but because there are better products available at the market, is mentioned by Bayus (1988). He suggests that, for many technology products, the decision to replace is influenced by price decline, product improvements or promotion, and analyzes upgrades using actual sales data. He focuses on evaluating the impact of firms' activities on upgrades but does not propose a model for forecasting repeat purchase. Steffens (2002) proposes a diffusion model that includes repurchase and points to the fact that the replacement rate can be accelerated if a product's feature changes. However, the repurchase is estimated as a function of time, and not as a function of utility improvements, which may still be useful for methods based on data fitting.

In our model we refer explicitly to utility and estimate repurchase based on surveys of a product's evaluation and purchase intentions for forecasting adoption and repurchase. We relate upgrading probability and repeat purchase to utility difference, see Eqs. (4-9) and (4-10). The probability of repurchase as a function of the difference between the utility of the owned product and that of available products, $P(\Delta u)$, which is product-specific, determines the repurchase nature and its role in the diffusion of the product.

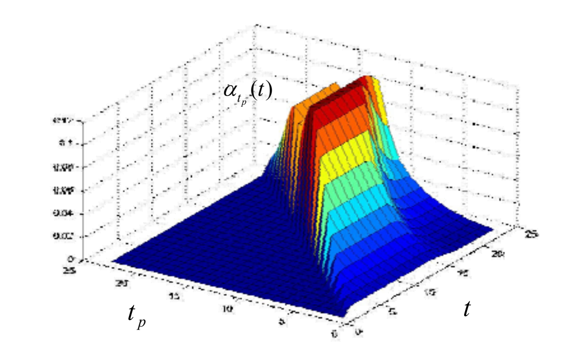
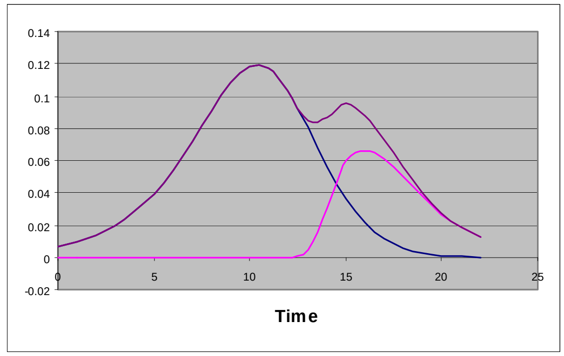
We assume that a customer will consider a repurchase only if the difference in utility between the product that is currently owned and a newer product available in the market, is larger than a threshold U_T. As the utility difference increases the likelihood of repurchase, or the number of customers who upgrade at this utility difference, rises as well. Beyond a certain utility difference the likelihood declines since most customers have already upgraded. The probability density function of the number of customers who upgrade at each utility difference can be found empirically by running a histogram on a survey data. We use a shifted Rayleigh distribution (with a probability density $f(\Delta u) = \frac{\Delta u}{\sigma^2} \cdot e^{-\left(\frac{\Delta u - U_T}{\sigma}\right)^2}\; ; \Delta u > U_T$), with different parameters, to demonstrate the impact of the upgrading probability on diffusion. Under the shifted Rayleigh distribution assumption the probability that a customer who considers upgrading will actually upgrade at period *t* is:

$$P_u\left(u^u(t) - u^u(t_p)\right) = e^{-\frac{\left(u^u(t-1) - u^u(u_{t_p}) - U_T\right)^2}{2\sigma^2}} - e^{-\frac{\left(u^u(t) - u^u(u_{t_p}) - U_T\right)^2}{2\sigma^2}} \; ; t_p < t, u^u(t) - u^u(t_p) > U_T . \qquad (5\text{-}9)$$

In the following examples we use the same parameters as in Eqs. (5-6a-c) and Eqs. (5-8a-c), and change the parameters of the shifted Rayleigh distribution, U_T and σ. The threshold U_T represents the strength of the drive to purchase and σ represents the diversity of the population in their tendency to upgrade. For each example we present the $\alpha_{t_t}(t)$ function, which represents those who purchased at t_p and did not upgrade until period *t*. The total sales are calculated using Eq. (4-8) while repurchase is calculated using Eqs. (4-10), (4-11) and (4-12). We also present sales component, adoption and repurchase, as we did with repurchase due to wear-out.

Example 14: Repeat purchase due to upgrade with threshold $U_T = 0.45$ and $\sigma = 0.1$.

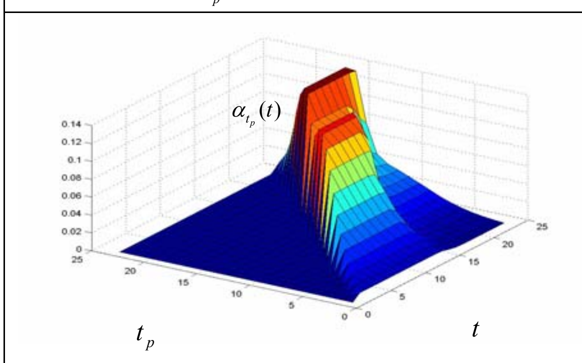
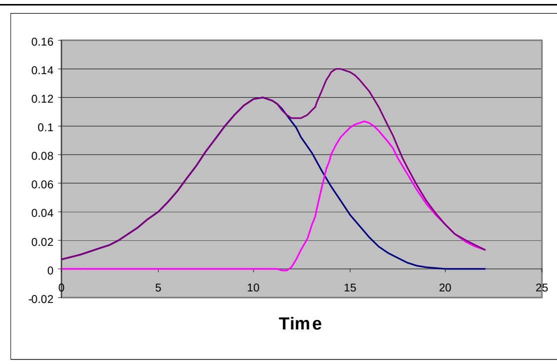
$$(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad U_T, \quad \sigma) = (1.053, 0.64, -0.76, 0.728, 0.45, 0.1). \qquad (5\text{-}10a)$$

The resulting $\alpha_{t_p}(t)$ is	Adoption $\dot{f}^w(t)$ / Repurchase $r^w(t)$ / Sales $s^w(t)$
	
We see that $\alpha_{t_t}(t)$ starts at the diagonal $t = t_p$, remains flat until $\Delta u > U_T$, and then declines quickly	Adoption Repurchase Sales

In *Example 15* we keep the same population diversity σ and increase the tendency to upgrade (a smaller threshold U_T). We see a stronger repurchase effect.

Example 15: Repeat purchase due to upgrade with threshold $U_T = 0.4$ and $\sigma = 0.1$.

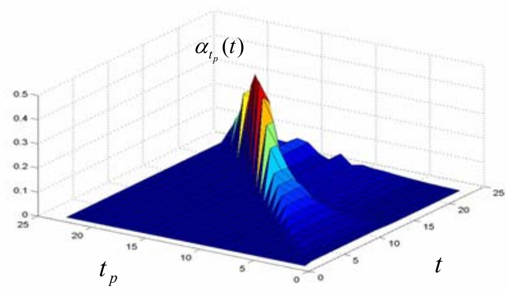
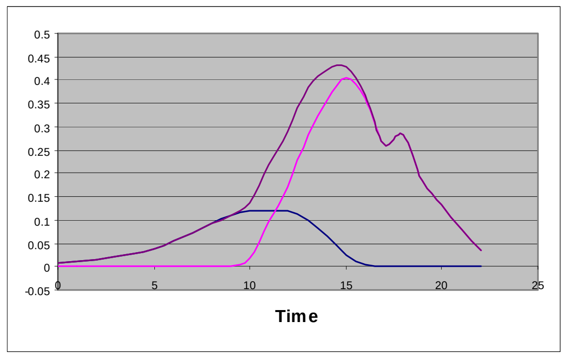
$$(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad U_T, \quad \sigma) = (1.053, 0.64, -0.76, 0.728, 0.4, 0.1). \qquad (5\text{-}10b)$$

The resulting $\alpha_{t_p}(t)$ is	Adoption $\dot{f}^w(t)$ / Repurchase $r^w(t)$ / Sales $s^w(t)$
	
We see that $\alpha_{t_t}(t)$ starts at the diagonal $t = t_p$, remains flat until $\Delta u > U_T$, and then declines quickly	Adoption Repurchase Sales

In *Example 16* we still keep the same population diversity σ and increase the tendency to upgrade further (a smaller threshold U_T). We see that the repurchase effect becomes stronger than adoption. The steep slopes of $\alpha_{t_p}(t)$ represent the fact that customers possess their product for shorter times until they upgrade to more advanced products

Example 16: Repeat purchase due to upgrade with threshold $U_T = 0.2$ and $\sigma = 0.1$.

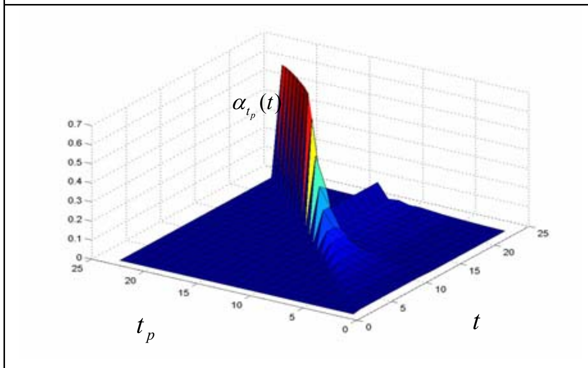
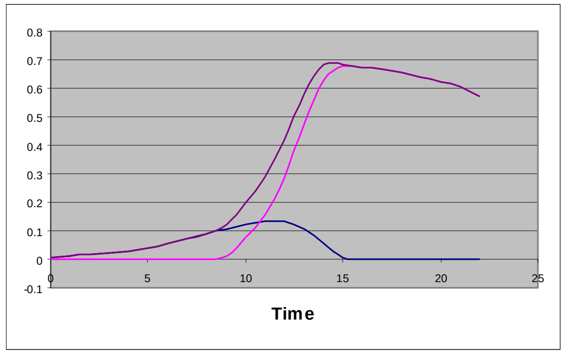
$$(u_0, \quad b, \quad \Phi_0, \quad \beta, \quad U_T, \quad \sigma) = (1.053, 0.64, -0.76, 0.728, 0.2, 0.1). \tag{5-10c}$$

The resulting $\alpha_{t_p}(t)$ is	Adoption $\dot{f}^w(t)$ / Repurchase $r^w(t)$ / Sales $s^w(t)$
	
We see that $\alpha_{t_t}(t)$ starts at the diagonal $t = t_p$, remains flat until $\Delta u > U_T$, and then declines quickly	Adoption Repurchase Sales

In *Example 17* we keep the same σ and increase the tendency to upgrade to even stronger values (a smaller threshold U_T). We see that the repurchase effect maintains the peak, or maturity, for a long time. The slopes of $\alpha_{t_p}(t)$ become steeper representing an even shorter time to upgrade

Example 17: Repeat purchase due to upgrade with threshold $U_T = 0.14$ and $\sigma = 0.1$.

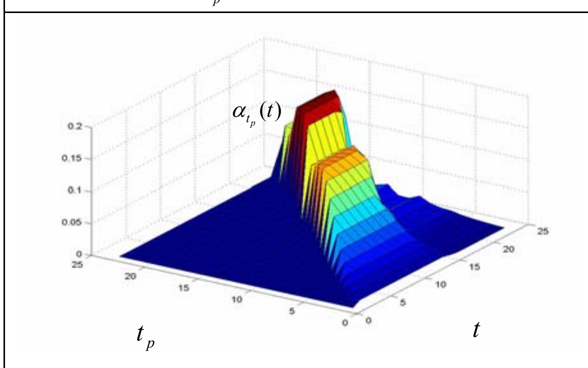
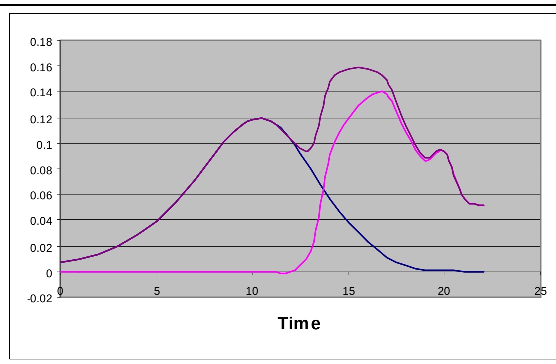
$$(u_0,\ \ b,\ \ \Phi_0,\ \ \beta,\ \ U_T,\ \ \sigma) = (1.053, 0.64, -0.76, 0.728, 0.14, 0.1). \qquad (5\text{-}10d)$$

The resulting $\alpha_{t_p}(t)$ is	Adoption $\dot{f}^w(t)$ / Repurchase $r^w(t)$ / Sales $s^w(t)$
	
We see that $\alpha_{t_t}(t)$ starts at the diagonal $t = t_p$, remains flat until $\Delta u > U_T$, and then declines quickly	Adoption Repurchase Sales

In *Example 18* we use the same threshold, U_T, as in Eq. (5-6a) but change the diversity of the tendency to upgrade of the population.

Example 18: Repeat purchase due to upgrade with threshold $U_T = 0.45$ and $\sigma = 0.05$.

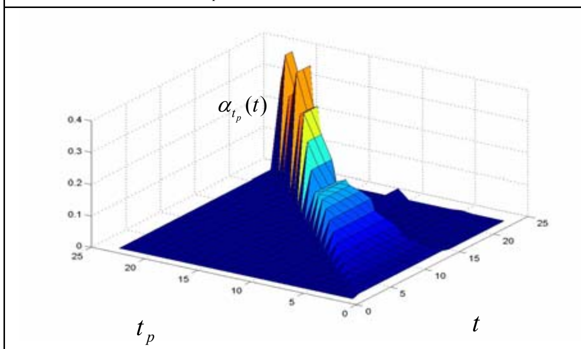
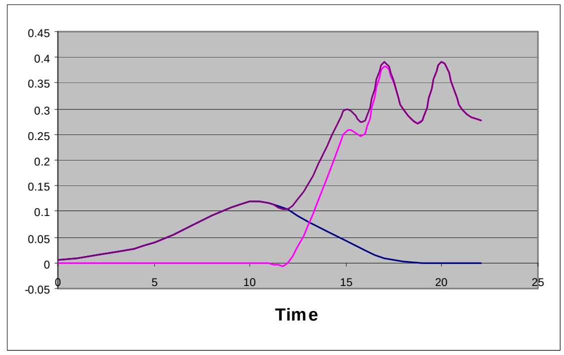
$$(u_0,\ \ b,\ \ \Phi_0,\ \ \beta,\ \ U_T,\ \ \sigma) = (1.053, 0.64, -0.76, 0.728, 0.45, 0.05). \qquad (5\text{-}11a)$$

The resulting $\alpha_{t_p}(t)$ is	Adoption $\dot{f}^w(t)$ / Repurchase $r^w(t)$ / Sales $s^w(t)$
	
We see that $\alpha_{t_t}(t)$ starts at the diagonal $t = t_p$, remains flat until $\Delta u > U_T$, and then declines quickly	Adoption Repurchase Sales

In *Example 19* we use again the same threshold, U_T, as in Eq. (5-6a) but reduce the diversity of the tendency of the population to upgrade. This reduction of the diversity causes sales to oscillate, as in the case of deterministic lifetime, see Eqs. (5-6b) and (5-6c).

Example 19: Repeat purchase due to upgrade with threshold $U_T = 0.45$ and $\sigma = 0.01$.

$$\left(u_0,\quad b,\quad \Phi_0,\quad \beta,\quad U_T,\quad \sigma\right) = (1.053,\ 0.64,\ -0.76,\ 0.728,\ 0.45,\ 0.01). \tag{5-11b}$$

<table>
<tr><td>The resulting $\alpha_{t_p}(t)$ is</td><td>Adoption $\dot{f}^{w}(t)$ / Repurchase $r^{w}(t)$ / Sales $s^{w}(t)$</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>We see that $\alpha_{t_t}(t)$ starts at the diagonal $t = t_p$, remains flat until $\Delta u > U_T$, and then declines quickly</td><td>Adoption
Repurchase
Sales</td></tr>
</table>

We have demonstrated that the proposed method can describe a diverse set of diffusion scenarios and market developments, depending on the parameters' values and the nature of repurchase. The challenge that we meet in the next two chapters goes beyond using speculated parameters to describe various scenarios or estimating the parameters to achieve a good fit to actual sales. The forecasting challenge is to estimate these parameters based on data that can be collected pre-launch or at the beginning of the product life cycle. An implementation of the model, including estimating the parameters and generating a forecast, is demonstrated in the next chapters.

6. Application of the Model to Pre-Launch Forecast - the Hybrid Car Case

In this chapter we demonstrate how we implement the model described in the previous sections, step by step, in the case of the hybrid car. We start with a brief of the background of the industry structure, inter-relations, and the relations with other industries, market size and other characteristics, the technologies involved and the interests and motivations of all parties (sections 6.1.1 to 6.1.6). Next we detail (sections 6.2.1 to 6.1.7) how we collected the data and processed it in a quantitative form to generate a market and technology forecast including the effect of both adoption and repeat purchase. We do not verify our forecast against actual sales since we lack actual sales data. Hybrid cars are still at a very early stage and advanced hybrids' generations are not launched yet. We cannot use forecasts generated by other diffusion models as a reference, since available sales data, used in these models, are not sufficient for estimating the diffusion model parameters based on regression and certainly not for the more advanced hybrids' generations which are not launched yet. We perform a sensitivity analysis for evaluating the robustness of the model to parameter variations. The market data and some of the technical data for this case were taken from the reports found in Graham (2001).

6.1 Hybrid Car Technology and Market Background

Global warming, air pollution and the decrease in oil reserves have raised public interest in electric cars. Electric and hybrid are far less polluting than internal combustion cars, even when the electricity for recharging the batteries is generated by burning fossil fuel. Several attempts have been made in this direction, but only recently have hybrid cars, which combine internal combustion and electric propulsion, become a real product. In 2006 hybrid cars reached about 1.5% of the overall car sales in US in 2006 and 2.25% in 2007. There are approximately 740 million automobiles in use worldwide and more than 200 million on US roads. Annual worldwide sales are around 60 million cars, about 17 millions in US, and sales of more than $2 trillion. The opportunities, as well as challenges are great. In this section we present a method of forecasting hybrid and electric cars sales and technology evolution for the next decade using our utility-based diffusion model presented in chapter 2. We will also present forecasts for the following two decades including adoption and repeat purchase. First, we briefly review the technology and then present the market status and firms' plans and roadmaps. Next, we present the industry structure and the major players and analyze the economic connections between them. Finally we use this analysis and a conjoint study to implement it in our model and generate a forecast.

6.1.1 Hybrid and Electric Cars Technology

Hybrid and electric car adoption is influenced by their utility which is composed of the features they offer. Hybrid car advantages are reduced emission and reduced operational cost. The reduced operational cost is achieved mainly by fuel savings but also from the lower cost of the mechanical systems maintenance. The disadvantage is the car price. In other aspects, such as performance and comfort, hybrid cars are comparable to conventional cars or slightly better. Electric cars offer zero emission, drastic reduced operational cost (electricity is far cheaper than fuel and an electric car wears out slowly) and quiet operation. Electric cars cost much more than hybrids (due to battery cost) and also have a limited range since fast-recharge infrastructure has not yet been deployed.

Electric car technology relies on electric motors and batteries. The electric motors available today are far more energy efficient, smaller, cheaper, easier to control, more reliable and provide better torque than internal combustion engines. Other components, such as the inverter, the control system, regenerative breaking and recharge systems, use mature technology and provide satisfying performance. Batteries are the weak point of electric vehicles since their energy density is about 3% of gasoline and they are very expensive (a battery for a mid-size sedan today costs 300$/mile so that a battery required for a 100 miles range today costs approximately 30,000$). Another problem with electric cars is the lack of recharge infrastructure. Other problems of electric vehicles, such as long recharge time and the large weight of the batteries had already been solved by modern batteries.

Hybrid cars combine the benefits of internal combustion engine technology and electric car technology. Instead of including a large, heavy and expensive battery, hybrid cars use a small battery that can drive the car for only a short distance and usually at a low speed. In hybrid cars the battery is recharged by a generator. The generator is propelled by an Internal Combustion Engine (ICE) that provides the power for the car at high speed. Having a generator on-board removes the range limit since hybrid cars do not need to recharge from the grid but use gasoline for on-board refueling. The electric motor is used for acceleration and assists the main engine in hill climbing situations, allowing the use of smaller and more efficient ICE. Internal combustion engines are relatively efficient at constant navigation speed but become very inefficient when accelerating or starting. Using the electric motor for acceleration causes a large saving in fuel. The ICE can also be shutdown when the car stops, since the car can start moving without waiting for the ICE to restart and gain power. Shutting down the engine at stops saves a lot of fuel when driving in the city compared to a regular car the engine of which consumes quite a lot of fuel when idling. Hybrid cars can also retrieve some of the kinetic energy while decelerating or going down a hill. They save approximately 30% of the fuel (thus producing less pollution) compared to a conventional car with similar performance. More advanced hybrid cars (plug-in hybrid) are planned to incorporate larger batteries that will allow the car to run for a significant distance on electricity alone and will provide the option of recharging the battery from the grid. Such cars will save up to 60% of fuel compared to regular cars.

Electric cars, whether powered by batteries, super-capacitors or fuel cells, are foreseen by all car manufacturers as the final goal. Electric cars have zero emission and do not use fuel at all. They also have a much simpler (thus cheaper and more reliable) transmission than regular car and certainly than hybrid cars that need to combine power from two sources, the electric motor and the ICE. Electric cars use only an electric motor so they do not need ICE auxiliaries, such as fuel tank, filters, cooling system, lubrication, exhaust and a tailpipe, that are needed in a hybrid car or an ICE car. The obstacles to electric car technology are battery cost and lifetime. There are three optional battery technologies that are considered for use in cars: lithium-ion batteries, super capacitors and fuel cells.

Lithium-ion batteries have high energy density and have been widely used in laptops and cell phones for a long time. In order to adjust lithium-ion batteries for use in electric cars, manufacturers needed to upscale and improve them in terms of cost and lifetime (an ordinary Lithium battery's lifetime is 3-5 years -- good for cell phones but not for cars). Battery manufacturers, who are aware of the emerging market of electric cars, are investing a lot of effort in improving batteries and making them attractive for use in cars.

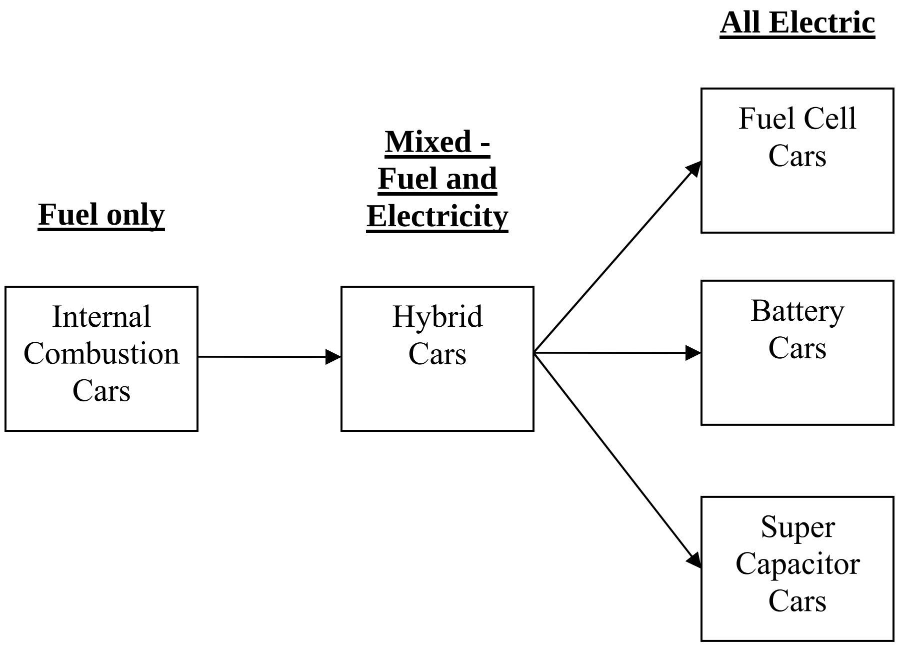
Super-capacitors constitute energy storage, like batteries, but with practically unlimited lifetime. Until lately, energy densities of super-capacitors were much lower than batteries in general and lithium-ion batteries in particular. Some breakthroughs in super-capacitors were announced by firms such as EEstore and Y-Carbon. There is a debate about the level of maturity that super-capacitors may reach in the foreseeable future.

The development of fuel cells is driven by some car manufacturers. A fuel cell generates electricity from a chemical reaction between hydrogen, stored in a high pressure tank, and oxygen from the air. The challenge of fuel cells is to develop a high power, rather than energy[15] density as in batteries, at a low cost. Other challenges are the safety issues presented by the high pressure tank. Unlike batteries or super-capacitors cars which can be recharged from the grid, fuel cells cars are fueled at a hydrogen gas station in a similar way to fueling regular cars at a gas station. Some experimental hydrogen gas stations are operational in several locations. The production of hydrogen and the deployment hydrogen gas stations are challenges that firms promoting this technology will need to meet in order to market fuel cell cars is high quantities. Fuel cells cars do not have zero emission but a clean emission that contains only pure water that does not have any negative impact

[15] The energy of the fuel cell is stored in the high pressure hydrogen tank.

on the environment. In our paper we refer to fuel cells cars as zero emission cars. The optional evolution paths of hybrid and electric cars are described in Figure 9.

Figure 9: Hybrids' Optional Evolution Paths



6.1.2 Market Status

Hybrid vehicles are (in 2007) still in the introductory stage. Toyota dominates the market with a more than 60% market share. Honda and Ford are far behind but have a significant market share while others have just joined or plan to join the hybrid game. The overall penetration of hybrid cars in 2006 was less than 1.5% of the car market which increased to 2.25% in 2007. Hybrids premium price, in 2007, is about $6000 compared to conventional cars. Analysts, such as Raskin and Shah (2006), and firms expect heavy duty car users, who have an acute need to increase car fuel efficiency, to be the first adopters in addition to environmentally aware customers. These customers are willing to pay premium price for the hybrid technology that reduces emission and provides more mpg (miles per gallon) then ICE cars. Indeed, taxi companies were among the first to adopt hybrids.

6.1.3 Industry Structure

The vertical structure for the hybrid car industry is quite simple. The major mechanical systems, including engine and its auxiliaries, transmission, steering, body and safety systems, which are common also to conventional cars, are usually designed and manufactured in-house by each brand[16]. Non-critical systems or commodity components for the major systems are supplied by external suppliers. The electric power components required for hybrids, and particularly the batteries, are supplied by a few high-tech firms. The dependency on external suppliers for major systems differentiates between conventional and hybrid cars industry structures.

The horizontal structure of the hybrid car industry includes Toyota as a market leader, Honda and Ford in the second-tier and several other late-comers in the third-tier. New entrants such as Tesla motors, Phoenix motorcars and ZENN focus on electric cars. Firms such as GM and Mitsubishi are also seeking new ways to join the hybrid trend with innovative ideas.

6.1.4 The Policies of Industry Players

A change in technology poses a threat to existing corporations, and internal operations in firms, since it forces them to invest in a new technology and change the way things were done for a long time. At the same time a technology change lowers entry barriers since old technology knowledge and expertise becomes partially irrelevant. Digital photography forced camera firms to acquire knowledge of sensors and electronics, while their knowledge of fine mechanics became obsolete. In a similar way, electric car technology forces car manufacturers to acquire knowledge of batteries, electric motors and control systems. At the same time it may lower entry barriers by making mechanical engineering expertise (engines, transmission) obsolete.

Toyota's activities seem to be aimed[17] to protect its leading position which relies on mechanical engineering excellence. Toyota's hybrids' high efficiency is achieved by using the electric motor and the ICE simultaneously relying on a sophisticated transmission, which is not easy to imitate. Toyota diversifies it hybrid product line and offers hybrid sedans, SUVs and luxury cars. Toyota has discontinued its RAV4 EV electric SUV (after selling 300 vehicles in 2002 for $42,000) which could have reduced the importance of the mechanical system's quality in cars. It keeps using old NiMH technology batteries, not only for conservatism, but also to slow Lithium battery development. Toyota is developing plug-in hybrids, which incorporate Lithium batteries, but is delaying their launch to market, probably until competitors offer their plug-in hybrids.

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[16] Sometimes there is a joint effort for body or engine as in the case of Mazda-Ford and Nissan-Renault
[17] As speculated based on its interests, behavior and managers' public statements

General Motors has fewer sentiments about the complex mechanical power train. It is developing the Volt, a plug-in hybrid, and had signed contracts with batteries suppliers (A123 and SAFT) to finance their development programs jointly. Mitsubishi, which is not one of the leading car marketers in the US but is strong in electronic devices, is developing an electric car which can promote its position in the car market.

Tesla is a new entrant in the car business but is the first to offer a commercial all-electric car. In order to mitigate the challenge of the high cost of the battery its focuses on sport cars. The high performance requirements provide an advantage to electric traction[18] which compensates the high battery cost. The volumes of sport cars are low, an advantage for new entrants, and they are not very sensitive to price. For the sport cars segment, the electric car offered by Tesla-motors is competitive in both performance and price. According to Tesla's chairman Elon Musk, Tesla intends to extend to other segments by launching luxury sedans in high volumes and by offering its battery pack to other electric car manufacturers. Several other new entrants, such as Phoenix-motorcars, ZAP-APX, Electrovaya and others, plan to join the market in the near future.

Car manufacturers have developed close relationship with battery suppliers. Panasonic supplies to Toyota and is partly owned by it. GM has signed contracts with A123 and Saft for developing batteries for it cars. Phoenix motorcars is partly owned by its supplier, ALTI. Electrovaya produces both batteries and cars. Similar relations exist in other industries such as mobile phones where Nokia and TI compete against Motorola and Freescale and Samsung and Agere[19]. Such relationships are flexible and car manufacturers will probably diversify their suppliers to avoid short supply or for technical reasons.

Infrastructure for recharging electric and plug-in hybrid cars has not yet been deployed. Users are expected to recharge their vehicles at home. When electric cars become more common, recharging services will probably be offered at malls, restaurants, parking places and maybe even gas stations. Some service firms, such as Project Better Place of Shai Aggasi, who foresees the widespread adoption of plug-in hybrids and electric cars, plan to deploy recharging infrastructure even before such cars are introduced to the market. The spread of recharging services, accompanied by a drop in the prices of electric and plug-in hybrids will encourage their adoption.

---

[18] ICE sport cars need a very powerful, expensive and heavy engine. An electric motor with the same performance is much cheaper, smaller and lighter

[19] The mobile phone devices division of Agere/LSI was acquired by Infineon in 2008. The acquisition made Infineon the primary supplier for Samsung mobile phones.

6.1.5 Market Attitudes Towards Hybrid/Electric Cars

The Electric Power Research Institute (EPRI) conducted a thorough market research of hybrid electric cars. Graham's (2001) report summarizes EPRI market research results. Its findings indicate that customers are willing to pay premium price for a hybrid/electric car, to reduce emissions, if it does not impact performance too much. Weber (2006) notes that customers tend to purchase within the vehicle segment that best suits their lifestyle. It seems that the sports car segment will be the first to switch to all-electric since the electric car technology in 2008 is superior to ICE in satisfying the requirements of this segment, in all aspects. Indeed, there are several sports car firms who have announced near-term plans of introducing electric sports cars to the market. A similar phenomenon of a new technology starting its penetration from a selective niche happened for digital photography technology where Polaroid cameras' customers were the first segment that switched to digital photography. Other car market segments will probably favor hybrids and plug-in hybrids for a while due to their more attractive prices. As the premium price and uncertainty of all electric cars are reduced and recharging services become more common, more market segments will switch to all-electric.

6.1.6 Battery Evolution

The evolution of batteries is the key to hybrid and electric vehicles' success. Other components, such as electric motors, inverters, electric breaking and controllers will also improve as the market grows and make the electric power train more attractive, but their influence is minor relative to improvements in batteries. The reason for this is that batteries must improve in order to make hybrid and electric vehicles attractive, while other components' features are satisfying and their improvement is "nice-to-have" but not critical.

Rechargeable batteries have existed for more than a centaury. The lead acid battery, which was already in use more than 100 years ago, is still in service with minor changes. Lead acid batteries are robust, reliable and cheap. Their drawbacks are high weight, small energy density, the long time it takes to recharge and the use of toxic materials. These drawbacks make the use of lead-acid batteries impractical for electric cars. An electric car with a reasonable range that uses lead-acid batteries would have to carry a huge and very heavy battery, which would impact its performance. The emergence of mobile applications, such as cellular phones and laptops, drove improvements in batteries and led to the development of NiMH and Lithium-Ion rechargeable batteries. These modern batteries have a much higher energy density and weigh a lot less, features that looked promising for use in cars. Still, problems such as short lifetime, self discharge, sensitivity to ambient conditions, long recharging time, high cost and safety issues made adjusting standard batteries for use in cars a real challenge. Note that for mobile application, these drawbacks were tolerated or irrelevant.

Table 1 presents the relevant battery features (true for 2005), based on Shukla (2005) and Balch et al. (2001). According to Table 1 Lithium batteries have advantages in energy density and efficiency, as well as disadvantages in durability and cost which caused hybrids manufacturers, until 2008, to favor NiMH.

Table 1: Battery Technologies Feature Comparison

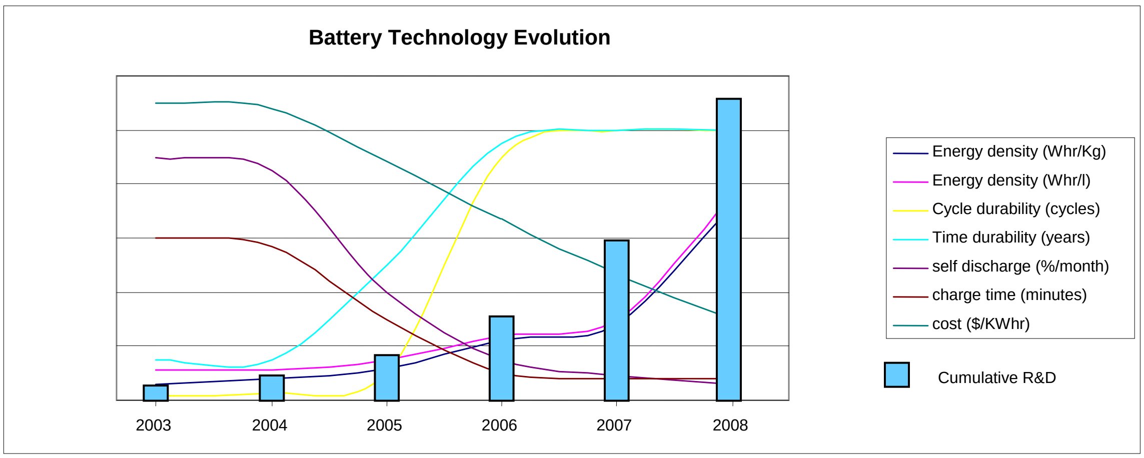
Lead Acid	Lead Acid	Nickel-cadmium	Nickel metal hydride	Lithium-ion	Lithium ion polymer	Nickel-zinc
Energy/weight (Wh/Kg)	30-40 Wh/kg	40-60 Wh/kg	30-80 Wh/kg	160 Wh/kg	130-200 Wh/kg	60 Wh/kg
Energy/size (Wh/L)	60-75 Wh/L	50-150 Wh/L	140-300 Wh/L	270 Wh/L	300 Wh/L	170 Wh/L
Power/weight (W/Kg)	180 W/kg	150 W/kg	250-1000 W/kg	1800 W/kg	1800 W/kg	900 W/kg
Charge/discharge efficiency	70%-92%	70%-90%	60%-70%	90%-99%	90%-99%	
Actual Energy Cost ($/KWh)	286	1000	2667	2857	2857	3000
Self-discharge rate	3%-20% /month	10%/month	30%/month (temperature dependant)	5%-10% /month	5%-10% /month	
Time durability	12 Months	12 Months	many years	30 Months	40 Months	
Cycle durability	800 cycles	2000 cycles	1000 cycles	500 cycles	500 cycles	300 cycles

NiMH batteries, which are still in use in hybrid vehicle, are inferior to Lithium-Ion in energy density, but have advantages in safety, power and ambient conditions. The low energy density, as well as long charging time, was worked around using the ICE to propel the vehicle and to recharge the battery while the electric motor only assists it. The cost issue led to the use of a small battery which enabled keeping the premium cost of hybrids within tolerable limits, at least for some customers.

A large battery is required to propel a car for a significant distance in electric-only mode. According to Shukla (2005), propelling a sedan requires 150-200Whr per mile or a battery of at least 15KWhr for 100 miles. Such a battery, in year 2000, would have cost $75000, been large and heavy (which would impact vehicle's performance), and would have required about 5 hours to recharge (quite annoying when a recharge is needed after 100 miles). Switching to Lithium-Ion technology, which solves volume and weight limit problems, requires solving other problems such as self discharge, safety issues and lifetime. A lot of R&D resources were invested to meet these challenges, which was finally achieved in 2007. Today there are several concept electric vehicle prototypes that are safe, convenient, high performance, high range and whose batteries are quickly rechargable. Cost, which still has a way to go, remains the only[20] major obstacle to electric cars becoming a mass product.

Firms are developing methods to improve battery features and lower the cost. Unlike NiMH, which uses rare and expensive materials, Lithium-Ion batteries are composed of relatively cheap materials and their high cost is due to the complexity of the production process. Significant progress has already been achieved and battery firms are working toward cutting costs further. Figure 10 presents the increase in R&D and the progress that has already been achieved in terms of batteries in the last five years.

Figure 10: Battery Technology Evolution



Since issues such as safety, lifetime, self-discharge and charge time seem to stabilize by 2008, batteries firms are likely to focus their R&D on the remaining problems. It seems that the major factors that will influence the transition of transportation to electric power are energy storage costs and the deployment of recharging infrastructure. The proliferattion of the recharging infrastructure and battery cost cuts will be influenced by market acceptance. It will depend first on the initial market which is willing to pay higher prices and will strengthen as market grows.

In the next section we describe step by step how we use technology, industry and market data to assess our model's parameters and generate a market and technology forecast for the next decade. By focusing on the major factors, and using some simplifying assumptions, it is possible to reduce the complexity and still generate a forecast that will capture the major trends. We provide an analysis of the forecast accuracy and its sensitivity to parameters variations.

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[20] There are still issues, such as manufacturing capacity, production line stability and standardization, that need to be solved. These issues are minor since the solutions are more procedural and not very risky.

6.2 Detailed Implementation of the Model to Hybrid Car

In this section, we implement the model described in the previous section for the case of hybrid cars. We use secondary data sources reported in Graham (2001).[21] We assume that the market is heterogeneous, thus using Eqs. (4-1), (4-2) and (4-3a), and that different customers have different preferences. A set of four representative hybrids types, with different combinations of attribute levels, represents the product line. Each market segment is a component of the market acceptance vector *f.* The attributes set, of two attributes per hybrid type, composes a (4×2) attributes matrix *A*. We refer to the influence of different hybrid types with different attribute combinations on the choices that different customers make, using the vector form of Eqs. (4-1), (4-2) and (4-3a). These choices change with the attributes due to technological progress. In the following we describe how we assess the attributes matrix *A(t)* as a function of the market vector *f(t)* and how sales vector $\dot{f}(t)$ is influenced by the consideration rate $\alpha(t)$, which is a scalar representing a uniform rate across hybrid market segments, and the market shares vector *m(A)*.

6.2.1 Description of the Hybrid Car Configurations

Following Graham (2001), we refer to a product line of four typical cars. These cars represent different levels of reliance on the innovative electric power train. While early hybrids, available in 2007, still rely mainly on fuel and are only assisted by electricity, more advanced hybrids rely almost or entirely on electricity. In the year 2007, only hybrids that are assisted by electricity are available. We expect that all types of hybrids will co-exist in the market for quite a long time to come. We analyzed all of the hybrid types together, rather than individually as separate products, since the different hybrid types share both the *market*, where customers decide which type of hybrid to choose, and the battery and electric power train *technology,* which is incorporated into all hybrids.

A purchase of a certain hybrid type is not independent of other hybrid types, but rather exclusive. If somebody buys a certain hybrid as a family car, s/he does not buy another hybrid type for the same purpose at the same time. Furthermore, the improvements in car attributes between the different hybrid types are not independent. The improvements in electric power train technology affect all hybrids cars. However, since the electric power train is more significant for the more

[21] Graham (2001) provides us with (a) conjoint study results and (b) technical breakdowns of car configuration costs, which enabled us to calculate the impact of batteries cost reduction on hybrids' overall cost.

advanced hybrids, the technology progress influences the advanced hybrid types more than the basic hybrid types. Following Graham (2001), we refer to a product line of four hybrid configurations according to their all-electric range:

1. The **HEV0** can run up to two miles on electricity only. The batteries are recharged by an on-board generator and cannot be recharged from the grid. The car uses the electric motor and the fuel engine simultaneously. All hybrids manufactured up to 2007 are of this type. These cars reduce pollution and fuel consumption by approximately 30% relative to conventional cars.

2. The **HEV20** can run up to 20 miles without using fuel. After using up the batteries, the HEV20 automatically switches to the fuel mode. It also switches to the fuel mode when the car is driven at highway speed. Such cars can be recharged from either an on-board generator or from the grid via a plug, and these vehicles are often referred to as 'plug-in' hybrids. Such cars can save up to 60% of the pollution and fuel consumption, depending on driving patterns.

3. The **HEV60** runs almost entirely on electricity and uses fuel only for long trips (more than 60 miles). Such cars will reduce pollution and gas consumption by 85%. They are referred to as 'serial' hybrids, since they always use their electric motor for propulsion, while the fuel engine, if used, is only for battery recharging. The battery can, and usually is, recharged from the grid.

4. The **BEV200** can be driven up to 200 miles before it needs to be recharged. Such cars do not have a fuel engine and use only electricity. Such cars have zero emissions and produce no pollution. The first cars of this type entered the market in mid-2008.

From now on, to simplify notation, we will identify the corresponding types **HEV0, HEV20, HEV60, BEV200,** with the indices *i=1,2,3,4,* respectively

.

6.2.2 Estimation of $\alpha(t)$

The purchase consideration frequency, $\alpha(t)$, is calculated from car market statistics. The introduction of attractive new hybrids will probably influence some of the customers who consider buying a car to choose a hybrid. The customers who do not consider purchasing a car at a certain time will continue to use their currently-owned car for that time period and will not be influenced by the new cars that are introduced in the market. At the time of the decision, the customer chooses between the available alternatives, including hybrids, according to the customer's needs, preferences, and available car attributes. Due to the high cost of a car, relative to other consumer products, we do not expect that car owners will dispose their cars just because an attractive hybrid is available. It is likely that customers will wait for the time they planned to replace their car and then consider the alternatives including hybrids. The annual car market in the US is around 17 million with a cumulative car market of about 241[22] million; thus, when referring to a period of one year,

$$\alpha = \frac{17}{241}\,. \tag{6-1}$$

Although the market displays seasonal behavior (stronger in summer and weaker in winter), the differences on a year-to-year basis are minor. The introduction of attractive new hybrids will probably encourage customers who consider buying a car (α per year) to choose a hybrid. The customers who do not consider purchasing a car at a certain time (the remaining $1-\alpha$) will continue to use their owned car for that time period and will not be influenced by the new cars that are introduced in the market.

6.2.3 The Attributes Set

For each hybrid car type *i, i=1,2,3,4,* we refer to a set of two attributes (A_{1i}, A_{2i}), where A_{1i} denotes the premium price of *i* relative to a conventional car, in short "premium price", and A_{2i} denotes the availability of hybrid models for *i*, in short "availability."

Graham (2001) ran a conjoint study under the assumption that there is a hybrid version for every car model; thus, he assumes 100% availability, which means that the respondents were asked to assume that every car model has a hybrid version of the specific type. According to this assumption, he determines the potential market of various hybrid configurations depending on attributes such as premium price, fuel price, and battery lifetime and replacement cost. We focus on premium price since the lifetime of Lithium batteries available in 2007, based on new materials and nanostructures, became long enough[23] to make the battery lifetime and replacement cost insignificant. For fuel price, we took a conservative assumption of stable prices. Fuel price rises will further accelerate the adoption of hybrids. This leaves premium price, which in any case was the most influencing factor, as a single parameter.

Weber (2006) claims that car customers tend to stick to their favored style. This means that a hybrid car will be considered by a customer only if there is a hybrid version similar to the conventional car s/he favors. We estimate that 100 car models will cover all the market segments; hence, we measure the availability by counting the number of available hybrid models and dividing it

[22] See USA Statistics in Brief--Energy, Transportation, and Communications 2005 at http://www.census.gov/compendia/statab/files/enercomm.html

[23] Batteries from Altairnano last more than 12 years. The Tesla Roadster battery warranty is for 5 years.

by 100. This estimation is rather conservative, since car manufacturers are likely to develop hybrid versions for popular models first, or models where hybrid technology offers more benefits.

6.2.4 Estimation of the Potential Market *m(A)* as a Function of the Attribute Levels

We estimate the potential market of each hybrid type as a function of its attributes. This estimation is based on Graham's (2001) conjoint study[24] with some adjustments. The study results are presented for each hybrid type separately, and ran under the assumption that there is a hybrid version for every car model, which means 100% availability. We adjust the results to refer to coexistence of several hybrid types and partial availability. We also extended the premium range by adding a minimum threshold for price premium at which everybody will prefer a hybrid over a conventional car[25]. Another addition is the BEV200 vehicle that will play an important role in the hybrid market. Its practical environmental benefits are similar to those of the HEV60, so we assume that the market refers to them similarly. The small difference is due to some economic advantage of the BEV200 in fuel savings. The clean appeal of the BEV200 as a car with no tailpipe is not included. On the other hand, we did not refer to the advantage of the HEV60 in terms of range. A range of 200 miles between recharges, when recharge time is 10 minutes, as in the Maya-100,[26] makes the range limit a minor issue.

We used a piece-wise linear function for interpolation. Detailed explanations of how Graham's (2001) conjoint analysis is summarized by Table 2 demand functions are given in Appendix B. In Table 2 we summarize the demand curves, or the potential markets dependency, on the first attribute, under the condition of 100% availability. We denote this dependency by $\tilde{m}_i(A_{1,i})$, i=1,2,3,4. However, as found by Weber (2006), even if a customer is willing to pay the price premium for the hybrid of her/his choice, it is necessary that a hybrid of this style will actually be available. In order to find the actual potential market, $\tilde{\tilde{m}}_i(A_{1,i}, A_{2,i})$, that also depends on the "availability" attribute, we multiply the numbers in Table 2 by the availability attribute and obtain:

$$\tilde{\tilde{m}}_i(A_{1,i}, A_{2,i}) = \tilde{m}_i(A_{1,i}) \cdot A_{2,i} \text{ , } \quad i=1,2,3,4. \tag{6-2a}$$

[24] The conjoint study sample included 400 respondents from Boston, Atlanta, Phoenix and Los Angeles. For more details see Graham (2001) report Chapter 2.7.2

[25] We believe that if the price premium of a hybrid is low enough to be returned (as fuel saving) within one year, even customers who do not care about the environment will favor hybrids.

[26] An electric car (Sport Utility Vehicle) marketed by Electrovaya in 2007 for $70,000.

Table 2 : Potential Market as a Demand Function of Price Premium *($A_{1,i}$)*

Hybrid Type	i	Potential market $\widetilde{m}_i(A_{i,j})$
HEV0	1	$\begin{cases} 1 & A_{1,1} < \$290 \\ 1 - 0.423 \cdot 10^{-3}(A_{1,1} - 290) & \$290 < A_{1,1} < \$2029 \\ 0.234 - 0.032 \cdot 10^{-3}(A_{1,1} - 2029) & \$2029 < A_{1,1} \end{cases}$
HEV20	2	$\begin{cases} 1 & A_{1,2} < \$478 \\ 1 - 0.282 \cdot 10^{-3}(A_{1,2} - 478) & \$478 < A_{1,2} < \$2991 \\ 0.258 - 0.030 \cdot 10^{-3}(A_{1,2} - 2991) & \$2991 < A_{1,2} \end{cases}$
HEV60	3	$\begin{cases} 1 & A_{1,3} < \$622 \\ 1 - 0.167 \cdot 10^{-3}(A_{1,3} - 622) & \$622 < A_{1,3} < \$5035 \\ 0.253 - 0.013 \cdot 10^{-3}(A_{1,3} - 5035) & \$5035 < A_{1,3} \end{cases}$
BEV200	4	$\begin{cases} 1 & A_{1,4} < \$887 \\ 1 - 0.144 \cdot 10^{-3}(A_{1,4} - 887) & \$887 < A_{1,4} < \$5982 \\ 0.264 - 0.011 \cdot 10^{-3}(A_{1,4} - 5982) & \$5982 < A_{1,4} \end{cases}$

Graham's (2001) conjoint study assumed that only one hybrid type is available as an alternative to ICE cars. When there are several hybrids, with different prices, that are available simultaneously, the market will be divided according to the environmental awareness segments. Those who are willing to pay more for clean vehicles will prefer the cleaner vehicles with the longer all-electric range. However, they may compromise on a less environmentally-friendly car if a better one is not available. Others who are willing to pay a lower premium will favor the lower cost and less environmentally-friendly vehicles[27]. We can say that the cleaner vehicle segments are a sub-group of the more polluting vehicles. This means that when we calculate the potential market share of each hybrid type, given the prices of each hybrid, we calculate the market share of the BEV200 first using the BEV200's price. Then we calculate the market share of both the HEV60 and the BEV200 using the HEV60's price. From this, we then subtract the share of the BEV200. In the same way, we calculate the market shares of both the HEV20 and the HEV0. In other words, we say that only a portion of the market is willing to pay a premium for low-end hybrids (HEV0) while others save and buy conventional cars. Out of the hybrids customers group, there is a smaller group of customers who are willing to pay an even higher premium for a more environment-friendly car (HEV20) if such is available. The same is true for the HEV60 and the BEV200. Thus, *m(A)* becomes:

[27] For example, the segment that is willing to buy an HEV60 at a higher price than an HEV20 would compromise on an HEV20 if the HEV60 is not available, but those who prefer HEV20 will not compromise on HEV60 if HEV20 is not available.

$$m(A)=\begin{pmatrix} m_1(A_{1,1},A_{2,1},A_{1,2},A_{2,2},A_{1,3},A_{2,3},A_{1,4},A_{2,4}) \\ m_2(A_{1,2},A_{2,2},A_{1,3},A_{2,3},A_{1,4},A_{2,4}) \\ m_3(A_{1,3},A_{2,3},A_{1,4},A_{2,4}) \\ m_4(A_{1,4},A_{2,4}) \end{pmatrix}=\begin{pmatrix} \tilde{\tilde{m}}_1(A_{1,1},A_{2,1})-\tilde{\tilde{m}}_2(A_{1,2},A_{2,2}) \\ \tilde{\tilde{m}}_2(A_{1,2},A_{2,2})-\tilde{\tilde{m}}_3(A_{1,3},A_{2,3}) \\ \tilde{\tilde{m}}_3(A_{1,3},A_{2,3)})-\tilde{\tilde{m}}_4(A_{1,4},A_{2,4}) \\ \tilde{\tilde{m}}_4(A_{1,4},A_{2,4}) \end{pmatrix}, \quad (6\text{-}2b)$$

where $\tilde{\tilde{m}}_i$, i=1,2,3,4, is as in Eq. (6-2a).

6.2.5 Cumulative Adoption Levels (in percentages)

Let $f=(f_1,f_2,f_3,f_4)$ be the vector representing the cumulative adoption levels (in percentages) of the four car configurations (HEV0, HEV20, HEV60, BEV200), which are assumed to be available simultaneously.

The periodic sales (in the number of cars) vector at time *t*, $n(t)=\left(n_1(t),n_2(t),n_3(t),n_4(t)\right)$ equals $\dot{f}(t)$ multiplied by the overall market size *M*. Or in discrete time, we assume that periodic sales $n_i(t)$ equals,

$$n_i(t)=M\cdot\Delta f_i(t)=M\cdot\left(f_i(t+1)-f_i(t)\right),\ \text{i=1,2,3,4.} \quad (6\text{-}3)$$

There are about 241 million[28] cars on the US roads, so for market size we set

$$\text{M=241 (in millions).} \quad (6\text{-}3a)$$

6.2.6 The Relationship Between Attributes and Adoption Levels *A(f)*

To calculate the dependency of car attributes on the level of adoption, *A(f)* (see *Assumption 2*), we analyze the technology and industry structure and processes as described below. In what follows, we will refer separately to each attribute.

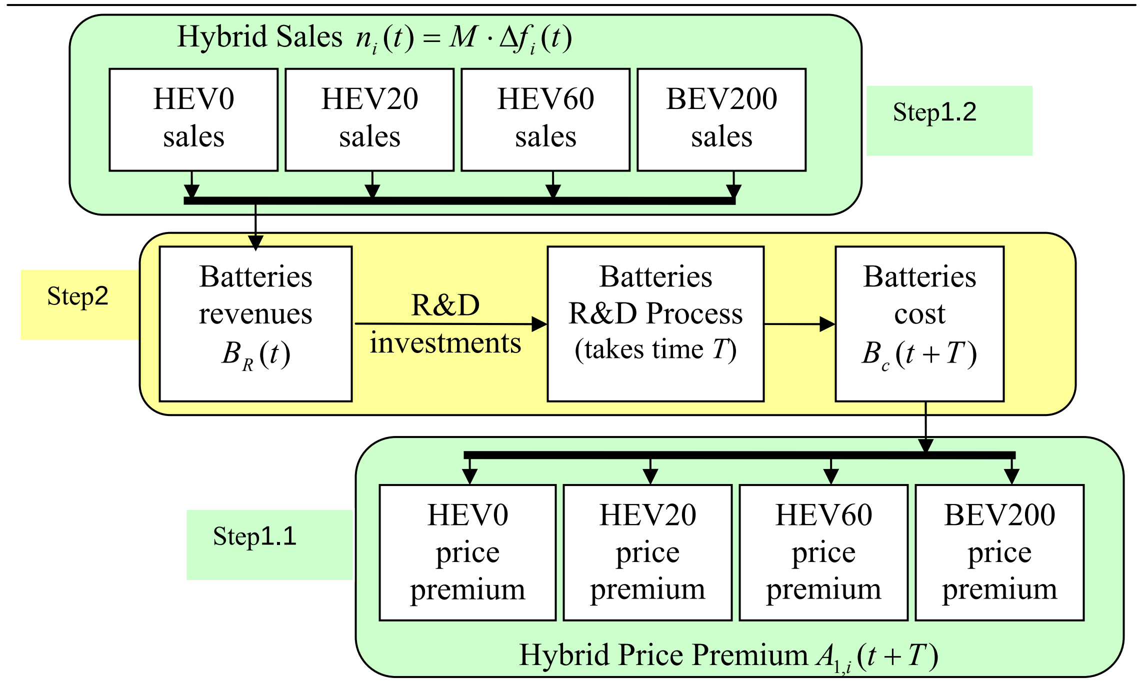
Price Premium and Adoption Level. Adoption influences the hybrid's price premium mainly through motivating and financing activities toward reducing battery cost. Battery cost is a major cause for the hybrid's price premium, especially for advanced hybrids which incorporate a large battery. Hybrid sales revenues are directed partially to battery manufacturers who supply these important components to the car manufacturers. The growing battery sales motivate and finance improvements of battery attributes, specifically further cost reductions. The reduced cost of batteries in a competitive hybrid car market is supposed to be reflected in the hybrid's final prices. The influence of battery costs on the hybrid's final price and on the portion of overall car revenues, which is directed to battery firms,

[28] See USA Statistics in Brief--Energy, Transportation, and Communications 2005.

differs according to the quantities of batteries that are incorporated in each hybrid type. The influence chain between hybrids' sales through battery cost to the hybrid's price premium is described in Figure 11. The competitive nature of the car industry[29] would cause prices to be linked to costs and avoid a situation where a monopoly can keep the prices high and increase its profits when component costs decrease. The markup, which is driven by the industry expenses structure, as explained in Graham (2001), is expected to remain stable.

We divided the attribute "price premium" of each hybrid into two components: One, which is considered to be constant,[30] and the other, influenced by the battery cost, say $B_c(t)$, which changes significantly over time. This cost is expected to decline with time (as the market grows) and to have a major impact on the car's price premium. The improvements of battery attributes in general, and specifically the decline in cost, are motivated by battery sales and revenues, say $B_R(t)$. The revenues $B_R(t)$ stem from hybrid sales, $n_i(t)$, i=1,2,3,4, since every hybrid incorporates a battery module component. Thus, we need to proceed in two steps (see Figure 11):

Figure 11: From Hybrid Sales to Hybrid Price Premium



29 The hybrid market, which in 2008 is still dominated by Toyota, attracts many competitors who have announced that they will joint this trend in 2009.

30 Although the price of other components, such as the motor and inverter, will also decline due to improvement and mass production, its impact on overall car price will be insignificant.

Step 1: To show how hybrids' price premium is influenced by battery costs (Step 1.1) and how hybrid sales influence battery revenues (Step 1.2).

Step 2: To show how battery cost is influenced by battery revenues through R&D. Since the R&D process takes time, the results of R&D at time *t* is reflected after a delay *T*, at time *t+T*.

Step 1.1: Price Premium and Battery Cost. To see how $A_{1,i}(t)$, i=1,2,3,4, depends on battery cost $B_c(t)$, we calculate the price premium of each hybrid type according to a breakdown of car components and their cost, detailed in Graham's report. The major components are the fuel engine, including all auxiliaries such as the cooling system, lubrication and fuel system, transmission (which includes the gear and the clutch), the electric motor (which also includes the inverter and the generator), and the glider (which includes the body, chassis and all other safety and comfort systems).

Following Graham's (2001) data, we assume a 1.75 markup - a factor that multiplies the overall components and assembly cost for price estimation. All the components, excluding the battery, are assumed to have a stable cost (see Footnote 9) so each car's premium is a function of the battery cost. The components' costs from Graham (2001) are detailed in Table 3. The calculation of the car's overall price includes the battery module cost. The cost of the battery module is a multiplication[31] of the battery cost, or the cost of the energy storage unit, by the battery module size or energy capacity of the module. The sum of components cost with battery excluded (from Table 3) and battery cost (from Table 4) are presented at the bottom row of Table 4.

[31] Although the cost of the battery module is not perfectly linear to energy capacity, we use linear approximation since in general the saving due to size is compensated by the enhanced safety measure required for a larger battery.

Table 3: Car Price Breakdown with Battery Excluded (The components with stable costs)

Car configuration	Conventional	HEV0	HEV20	HEV60	BEV200	Comments
Gas Engine	2357	1444	1370	1039	0	The gas engine is smaller and simpler in hybrids, since some of the power is provided by the electric motor.
+ Transmission	1045	1200	1200	625	400	The transmission in the parallel hybrids (HEV0, HEV20) is more complex, since it combines power from two sources.
+ Electric Motor	40	797	893	1213	1213	In more advance hybrids, the electric motor is larger, since it propels the car in all states.
+ Glider	7380	7580	7580	7580	7580	Basically the same for all cars. We added $200 for the hybrids' regenerative braking system.
= Total Cost	**10822**	**11021**	**11043**	**10457**	**9193**	**Simply a sum of the components**
Estimated baseline price (with battery excluded) with 1.75 markup	18984	19287	19325	18300	16088	Price = total cost * 1.75
Baseline Premium relative to a conventional car	0	303	341	-684	-2896	Note that without the battery advanced hybrids are cheaper than conventional cars. The battery cost is the origin of their high cost.
We assumed 1200 for parallel hybrid transmission (rather than 625 in Graham, 2001), since it is more complex than regular transmission. Glider cost is based on Graham (2001) 4.2.1.2.1 and includes accessories. We added $200 for regenerative brakes for all non-CV vehicles. Base price is based on Graham (2001) 5.2.4.2, which results in a 1.75 markup. Markup includes overhead, warranty, depreciation, sales cost, and profits.						

A battery module required for a car that has a long all-electric range needs to store more energy than that for a hybrid that has a short all-electric range.[32] Different car configurations use different battery sizes according to the car's size and all-electric range. The typical battery size is calculated, based on Shukla (2005), to be 200Whr per mile[33]. The battery size of each hybrid type is detailed in Table 4.

Table 4: Propulsion Battery Energy Storage Capacity (Size) and Hybrids' Price Premium

Car configuration	Conventional	HEV0	HEV20	HEV60	BEV200
Battery Size (KWhr)	0	0.5	4.5	13.5	40
Actual battery module cost with today's NiMH batteries' ($2200/KWhr) cost	0	$1,100	$9,900	$29,700	$88,000
Actual battery module cost ($) with varying battery cost ($/KWhr)	0	$0.5B_c(t)$	$4.5B_c(t)$	$13.5B_c(t)$	$40B_c(t)$
Hybrid premium ($) ($A_1$) based on battery module cost (line above) and baseline from Table 2	0	$0.5B_c(t)+303$	$4.5B_c(t)+341$	$13.5B_c(t)-684$	$40B_c(t)-2896$

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[32] We refer to a mid-size car. A larger car requires a larger battery than a smaller car.
[33] This is aligned with Electrovaya's 40KWhr battery that can propel the Maya-100 compact SUV for 200 miles.

The battery cost changes over time, due to battery R&D, and motivated by battery revenues. Table 4 also details the current cost of the battery module in 2007, which clarifies why in 2007 there are only hybrids of the HEV0 type, the varying module cost as a function of the battery cost per energy unit ($/KWhr), and the varying hybrid premium. Based on the last row of Table 4, we can calculate the hybrid premium $A_{1,i}$ as a function of battery cost $B_c(t)$, thus:

$$A_{1,i}(t) = \begin{cases} 0.5B_c(t) + 303 & i = 1 \\ 4.5B_c(t) + 341 & i = 2 \\ 13.5B_c(t) - 684 & i = 3 \\ 40B_c(t) - 2896 & i = 4 \end{cases} . \tag{6-4}$$

Step 1.2: Battery revenues as a function of hybrid sales. To complete Step 1, we must show the relation between the hybrid market growth and battery revenues. Battery revenues $B_R(t)$ are connected not only to the number of hybrids sold, but also (as shown in Table 4) to the type of hybrid. Battery revenues that stem from each hybrid type are a multiplication of the sales of that hybrid type, in units, by the battery size incorporated in each hybrid, and by battery cost. The overall battery revenue is the sum of the revenues that stem from each hybrid type's sales. Based on the first row of Table 4, we can link battery revenues $B_R(t)$ to hybrids sales, which is the sum of the multiplication of hybrids' sales of each type by the battery size incorporated in it, and by battery cost, according to the following relationship:

$$B_R(t) = B_c(t) \cdot \left(0.5n_1(t) + 4.5n_2(t) + 13.5n_3(t) + 40n_4(t)\right). \tag{6-5}$$

Step 1, which links hybrids' price premium to battery cost and hybrid sales to battery revenues, transforms the problem of linking the vector of hybrid premium to the vector of hybrid sales into a scalar relation between battery revenues $B_R(t)$ and cost $B_c(t)$. This relation will be further detailed in Step 2.

Step 2: Battery Revenues and Battery Cost. The first issue that we need to address is that of R&D, which, as it is driven by revenues and enables cost reduction, takes time. The new low-cost batteries based on today's R&D effort will be launched after some delayed time period *T*. We can say that battery cost at time *t+T*, $B_c(t+T)$, is based on R&D that is financed by revenues at time *t*, $B_R(t)$.

First, we assess the typical R&D cycle *T*. Industry experts and researchers estimate a typical R&D process of developing a full car battery module[34] to take up to two years. A more aggressive R&D plan, which means more R&D resources, leads to better product improvements, since several options, including those that are more promising but at that same time more risky, are considered concurrently. Still, although higher investments enable concurrent execution of several tasks, and result in an earlier final product, there is still a limit to how much development time may actually be shortened. Based on inputs from researchers and industry experts[35], we assess that time limit to be approximately two years. Most of the battery-related R&D efforts today are directed[36] at lowering the battery cost, which influences the price of the hybrid cars with longer all-electric range (the HEV60 and BEV200) more than the hybrid cars with shorter all-electric range (the HEV0 and HEV20). Other issues that once limited the use of batteries in cars, such as weight, recharge time, lifetime, sensitivity to ambient conditions, and limited power, have practically all been solved. Electric concept cars in 2007, such as Electrovaya's Maya-100, have a range of 200 miles between charges and can be recharged in 10 minutes. Altairnano's Lithium batteries can operate safely within a wide temperature range[37]. The battery cost reduction forecast is based on the past achievements of major battery developers over the last three years in developing new materials, processes, and battery packs, as well as on R&D investments during that time period. The cost of Lithium batteries[38] (in 2008) is about \$1,500/KWhr; further R&D will reduce the price even more[39]. DasGupta et al. (2005) evaluate that, based on the progress of materials and processes, prices will decline to \$300/KWhr within a few

[34] Developing a new battery involves: up-scaling a laboratory unit; solving thermal and robustness issues; designing a protective pack that provides a protective ambient, monitors the cells' operation, and controls the energy flow; and testing the module's performance and safety.

[35] See "Plug-In Hybrid Electric Vehicle R&D Plan" by FreedomCAR & Vehicle Technologies Program, US Department of Energy, February 2007. See also interview with Dr. Bart Riley, co-founder, VP of R&D and CTO of A123 Systems (http://www.gm-volt.com/2007/06/21/gm-volt-exclusive-interview-and-podcast-with-a123-co-founder-cto-and-vp-of-rd-bart-riley-on-building-the-volts-battery-pack/).

[36] Electric cars available today such as Maya-100 of Electrovaya, Phoenix SUV, ZAP X of APX and others have very appealing attributes and the only obstacle to mass adoption is vehicle cost (\$60000 and more) which stems from batteries cost. Also the only stated batteries R&D goal of DOE, quoted by Tien Duong from the FreedomCAR on Plug-in Hybrid Electric Vehicle (PHEV) Forum and Technical Roundtable held by California South Coast Air Quality Management District (AQMD) on July 12th 2006 referred to batteries cost.

[37] See "Safety First – The Story of why all Lithium Batteries are not the same" *Power Management Design Line* May 1 2007 by Evan House PhD and Fayth Ross MS, Altairnano Inc.

[38] Lithium batteries incorporated in the Tesla Roadster, Phoenix Motorcars SUT, and Electrovaya's Maya-100, which will be released at the beginning of 2008.

[39] Unlike NiMH batteries, used in today's hybrids, which use rare raw materials, Lithium batteries use abundant materials and their present high cost stems from the manufacturing process. As the hybrid and electric car market grows car battery sales will grow accordingly.

years[40]. Battery-related R&D investments will also grow with the market and encourage the development of lower-cost batteries.

In evaluating a battery's evolutionary path and rate, we made three assumptions:

(a) Cost reduction requires more effort as cost declines (see Söderholm and Sundqvist 2003; Neij 1999). This means that maintaining the same effort will cause a slowdown in the cost reduction rate. Alternatively, maintaining the same cost reduction rate requires an increase in effort. To account for the diminishing effects of the effort, we use a square root function for the relation between cost reduction impact and resources invested in it.

(b) Battery industry R&D will continue to focus on cost[41] until the benefits of cost reduction, in terms of market attractiveness, cease to be dominant. This means that R&D budgets, which are allocated as percentages[42] of sales, will mostly be directed at cost reduction.

(c) The evolutionary rate of the battery components is aligned with the overall evolutionary rate. This is a simplified assumption that refers to the average cost reduction. Referring to each component (such as pack and cells) separately may be slightly more accurate, but requires much more data and is more sensitive to noise.

Grant (2002) presents the law of experience where cost reduction usually follows an exponential curve. The simplest case is when the cost reduction rate is constant, in percentage. If battery costs keep declining by 30% each period, as they did in 2007, then $B_c(t) = 0.7 B_c(t-1)$. If we assume that the cost reduction rate is constant, then battery cost at each time is calculated as:

$$B_c(t) = B_c(0) \cdot 0.7^t \text{ , or } \log\bigl(B_c(t)\bigr) = \log\bigl(B_c(t-1)\bigr) + \log 0.7 = \log\bigl(B_c(0)\bigr) + t \log 0.7 \text{ .} \quad (6\text{-}6a)$$

[40] Battery module cost components are the pack cost, which in 2007 constituted 75% of the overall battery cost, and the cost of the cells. The pack includes the physical protective package and the electronic system that manages and monitors the energy flow. The design methods for such mechanical and electronic systems are well established and cost reduction procedures, when adjusting to mass production and updated processes, are routine. The cost reduction rate is determined by the investments in design. Another source for cost reduction of the pack is that advanced cells are more robust and relax the demands on the pack. The cost of the battery cells, which store the energy, stems from the material cost and from the cell manufacturing process. Many research labs are developing new cells, using new composites and new structures, based on nanotechnology. The new cells can store more energy in a given volume or mass and are also cheaper to produce. The challenge of a battery R&D manager is to choose the more promising lab cells and to convert them into a battery module that can be adapted to a car. This process is expensive and risky, since issues such as safety and lifetime are not observed in the lab cells and are only discovered during the conversion process. When R&D budgets increase several development paths are considered simultaneously, including more promising though more risky options, leading to better improvements.

[41] See FreedomCAR and Vehicle Technologies Program, U.S. Department of Energy goals presented by Tien Q. Duong on July 12, 2006 (http://www.aqmd.gov/TAO/ConferencesWorkshops/PHEV_Forum-07-12-06/3-TienDuong-DOE.pdf)

[42] The common policy of allocating R&D budgets as percentage of sales is supported by many firms' annual reports. It varies between industries but is similar and stable within each industry.

Following Söderholm and Sundqvist (2003) and Grant (2002), we assume that the learning curve does not follow a constant reduction rate path but rather is influenced by the cumulative R&D-based knowledge stock. When the cost reduction rate is not constant, but influenced by R&D investment, which is proportional to batteries' revenues $B_R(t)$, we replace the time multiplier of $\log 0.7$ at Eq. (6-6a), t, by the scaled cumulative revenues $\sum_{\tau=0}^{t} kB_R(\tau)$, where k is a scaling parameter that represents the basic response between revenues and cost attribute, and incorporates both the percentage of revenues allocated to R&D and R&D team capabilities. This can be calculated by instantiating the battery cost values of two successive periods, and the revenues that motivated this cost change.

Taking into account the diminishing effects, represented by the elasticity coefficient a as proposed by Grant (2002), we used a square root function[43] (see Assumption (a) above). We used a conservative value of $a=0.5$, rather than the common range 0.7-0.8 mentioned by Grant (2002), to represent a slower response of the battery technology progress to R&D investments. The slower response, relative to progress in other technologies, is due to the nature of battery technology progress which relies more on basic research and less on design. We also assumed a delay T between technology development and a launch to market due to the nature of the car industry and the delays caused by reliability and safety concerns. Thus, when Eq. (6-6a) is delayed by T, it becomes:

$$\log\big(B_c(t+T)\big) = \log\big(B_c(0)\big) + \sqrt{\sum_{\tau=0}^{t} kB_R(\tau)} \cdot \log 0.7 \,. \tag{6-6b}$$

We will later show that using other concave functions, instead of a square root in Eq. (6-6b), provides similar results for both the short- and mid-term forecasting.

Availability and Adoption Levels. For evaluating $A_{2,i}(f_i)$, $i=1,2,3,4$, we checked how much R&D is allocated for new cars development, and how much it costs to develop a new car model. Car manufacturers, such as Mitsubishi and Honda, allocate about 6% of sales to R&D. For the availability attribute, we did not assume a descending learning curve, as was done by Söderholm and Sundqvist (2003), and as we did for the battery case, since extending a product line does not become more difficult as diversity increases. We assess the availability of new hybrids, or the releasing of new hybrids models, as a function of previous periods' sales. Sales and revenues provide the motivation and resources for further development. Following Dahan and Hauser's (2001) funnel theory, we assume that the expenses for the final development stages are larger than earlier ones. As noted by Dahan and Hauser (2001), similar products, in our case the HEV60 and BEV200, can share

[43] A square root function is more restraining than the degradation filter used by Söderholm and Sundqvist (2003) and represents more tightly the fact that at lower cost it is more difficult to reduce cost further.

early development stages. We imply that a larger share of R&D budget is directed to short term plans and a smaller share to long term plans. Based on forecasted sales, we can estimate the R&D resources allocated for developing new hybrid car models; thus, we can assess the number of new hybrid car models that will be developed each year. Firms are assumed to monitor market preferences and direct their R&D efforts to developing hybrids of the types that are desired by the market. We take representative industry parameters values, and later analyze the impact of their variation using sensitivity analysis method. Taking a cost of $90,000,000 for car model development[44], $20,000 for car price[45], 6% of sales allocation for R&D[46], and a policy - following Dahan and Hauser's (2001) funnel theory - of investing 75% of R&D budget for the short term development plan[47] and 25% for the longer, two years development plan[48], we can assess the number of available car models in a certain year, given the sales of the preceding two years. We also assume that there is a limit of 60% to the growth of R&D teams' productivity due to the need to train skilled personnel. The R&D resources, $R\&D_i(t)$, allocated to diversifying the hybrids' product line of each hybrid type i is:

$$R\&D_i(t) = 20,000 \cdot .06 \cdot \left(0.75 n_i(t-1) + 0.25 n_i(t-2)\right) \quad , \quad i=1,2,3,4, \tag{6-7}$$

where $n_i(t)$ is as in Eq. (6-3). The total number of hybrid models at time *t*, which is the sum of the number available previously and the number of new hybrids models at time t, is calculated by

$$A_{2,i}(t) = A_{2,i}(t-1) + \frac{R\&D_i(t)}{R\&D\_\cos t} = A_{2,i}(t) + \frac{20,000 \cdot .06\left(0.75\dot{f}_i(t-1) + 0.25\dot{f}_i(t-2)\right) \cdot 241 \cdot 10^6}{90 \cdot 10^6}, \tag{6-8}$$

i=1,2,3,4.

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[44] This is the sum raised by Tesla Motors for developing the Tesla Roadster. Building an assembly line for mass produced vehicles will cost more but it will serve many car models.
[45] Using a rounding of the $18,984 basic vehicle reference price from Graham (2001)
[46] See Mitsubishi and Honda 2006 reports
[47] The partitioning of 75% and 25% is arbitrary. We checked that a different allocation, for example 80% and 20% or 60% and 40%, has a minor influence on the overall forecast.
[48] Tesla plans to sell the Whitestar model in two years from the beginning of its design.

6.2.7 Forecasting Hybrids Adoption

Forecasting adoption is based on the general formula (3a), when using the parameters and expressions which are specific to the hybrid case from Eqs. (6-1)-(6-8). Battery cost at the beginning of 2008, which is a result of cumulative R&D resources at the beginning of 2006, was 30%. Cumulative US sales of hybrids by the beginning of 2006 were 390,000[49]. Since all current hybrids on the road today are of the HEV0 type and incorporate a $1,100 NiMH battery[50], see Jones (2005), cumulative battery revenues by the beginning of 2006 were $430 million. The scaling parameter k of Eq. (6-6b) is calculated by instantiating battery prices from 2006 and 2008 and the cumulative battery revenue. When using the prices,[51] which are $2,200 and $1,500, respectively. We obtain:

$$k = \left(\frac{\log(1500) - \log(2200)}{\log(0.7)} \right)^2 \cdot \frac{1}{430} = 0.0026814 \,. \tag{6-9}$$

We present the price premium and availability of each hybrid type for every year in Table 5. Hybrids' premium in Table 4 is a function of battery cost and is calculated according to Eq. (6-4). The premium for the years 2005-2007 is taken from actual market data and is higher than the expected price as a function of battery cost, due to demand pressures and the lack of competition. The premium will decline gradually, due to increased competition, and we estimate that by 2010 competition will drive the hybrids' premium down to reflect costs with the ordinary profit markup. The numbers of hybrid models available until 2010, which can be considered initial values, are exogenous and based on manufacturers' announcements. From 2010 the number of hybrid models available is endogenous and estimated using Eqs. (6-7) and (6-8). Using the price premium of each hybrid type, $A_{1,i}$, from Table 5, in each year, we calculate the potential market for each year, $\tilde{m}_i(A_{1,i})$, under 100% availability assumption, based on the function of Table 2. We then scale it by actual availability, $A_{2,i}$, from Table 5 using Eq. (6-2a), to calculate the potential market under actual price premium and availability $\tilde{\tilde{m}}_i(A_{1,i}, A_{2,i})$. Finally, we calculate the real potential market $m(A)$

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[49] See Dave Hermance 2006 presentation at http://www.cargroup.org/mbs2006/documents/HERMANCE.pdf

[50] Although the battery module nominal capacity is 1.3KWHr it can use only 40% of its capacity (between 40% and 80%) which is effectively 0.5KWHr.

[51] The $2200 price at the end of 2005 is a quote of Dave Hermance, Toyota's chief engineer, interview to Willie D. Jones (2005). The $1500 in 2008 is the price of the batteries used in Electrovaya Maya-100 and Phoenix Motorcars SUT which are planned to be released in 2008.

considering price premium, availability and simultaneous presence of competing hybrid type using Eq. (6-2b). Sales $n_i(t)$ are calculated using Eqs. (4-3a), (6-1) and (6-3). The market results are presented in Table 6. The whole path of calculating $\tilde{m}_i(A_{1,i})$, $\tilde{\tilde{m}}_i(A_{1,i}, A_{2,i})$, $m(A)$ and sales is detailed in Appendix C.

Table 5: Hybrid/Electric Vehicles Attributes Development Forecast

Year	Battery cost ($/KWhr) $B_C(t)$	Premium ($) $A_{1,i}$				Availability (# of cars) $A_{2,i}$			
		HEV0	HEV20	HEV60	BEV	HEV0	HEV20	HEV60	BEV
2005	***2200***	***6000***				***5***			
2006	***2200***	***6000***				***9***			
2007	***2200***	***6000***				***15***			
2008	***1500***	4000			57104	18			***3***
2009	1349	2500	6411		51055	23	***11***		***5***
2010	1196	901	5722	15458	44933	29	***27***	***9***	***6***
2011	1076	841	5184	13845	40152	36	30	9	6
2012	753	679	3731	9486	27238	66	37	11	6
2013	527	566	2714	6435	18198	100	47	14	6
2014	369	487	2002	4299	11869	100	61	18	6
2015	258	432	1504	2804	7440	100	88	23	8
2016	181	393	1155	1758	4339	100	100	34	11
2017	127	366	911	1025	2168	100	100	58	15
2018	89	347	740	512	649	100	100	100	25

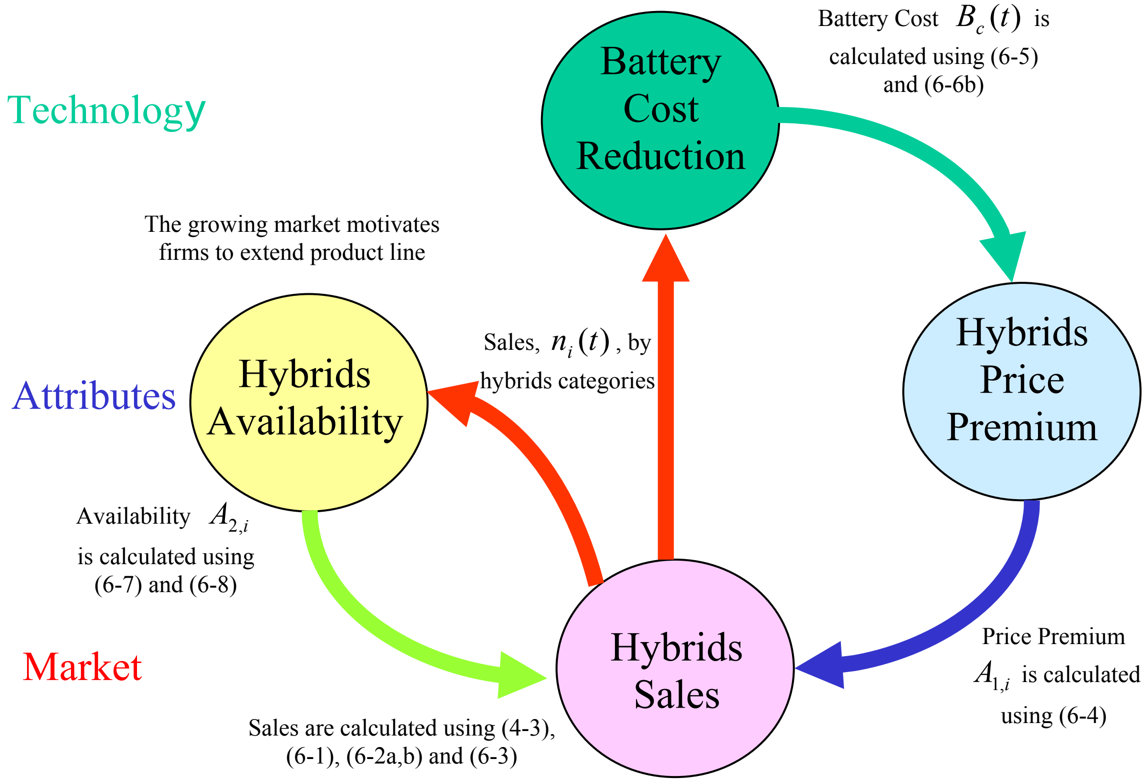
Table 6 also includes adoption fraction *f*, calculated by cumulative sales and divided by $M=241 \cdot 10^6$. Batteries' annual revenues are calculated using Eq. (6-5). Based on battery revenues from Table 6, we can assess cost reduction and battery costs after two years (typical battery development time) using Eq. (6-6b). We added a limit of 30% annual cost reduction, which embeds a claim that costs cannot be reduced beyond that rate even with unlimited resources. This means that we examine the values of $B_c(t)$ as resulting from Eqs. (6-6a) and (6-6b) and take the maximum cost, or minimum cost reduction rate, between them. This limit makes our estimates less sensitive to the specific learning curve chosen at Eq. (6-6b), since the limit of Eq. (6-6a) and not the R&D resources, for this specific case, determines the battery cost path after 2011. The assessed battery cost is presented in Table 5. The availability $A_{2,i}$ is assessed based on sales $n_i(t-1)$ and $n_i(t-2)$ from Table 6 using Eqs. (6-7) and (6-8). The number of hybrid models (availability) is also presented in Table 5. The division into Table 5 and Table 6 was incorporated for the sake of convenience; they should be referred to as a unified table.

Table 6: Hybrid/Electric Vehicles Market Development Forecast

	Sales, $n_i(t)$, $i=1,2,3,4$				Adoption fraction f				Batteries' revenues ($M)
Year	HEV0	HEV20	HEV60	BEV	HEV0	HEV20	HEV60	BEV	
2005	***205749***				0.0008537				226
2006	***247000***				0.0018786				272
2007	***352760***				0.0033424				388
2008	529,244			***200***	0.0055384			0.0000008	409
2009	548,621	291,538		***2000***	0.0078148	0.0012097		0.0000091	2247
2010	2,841,938	628,630	181,890	***5000***	0.0196071	0.0038181	0.0007547	0.0000299	8257
2011	3,696,179	764,781	213,790	***7500***	0.0349439	0.0069915	0.0016418	0.0000610	9122
2012	7,717,724	1,128,480	331,440	29,324	0.0669677	0.0116740	0.0030171	0.0001827	10987
2013	11,333,234	2,381,205	407,615	135,454	0.1139936	0.0215545	0.0047084	0.0007447	14398
2014	8,645,817	4,645,691	940,978	220,118	0.1498683	0.0408312	0.0086129	0.0016581	17252
2015	4,546,508	7,908,784	2,123,882	335,704	0.1687335	0.0736478	0.0174257	0.0030510	20663
2016	2,099,303	8,500,543	3,675,859	906,529	0.1774443	0.1089197	0.0326782	0.0068126	22644
2017	1,268,338	5,139,665	6,956,672	2,032,724	0.1827071	0.1302461	0.0615441	0.0152471	25195
2018	697,569	0	12,056,993	4,187,472	0.1856016	0.1302461	0.1115731	0.0326225	29303

Pagani (2008) describes the mutual influence between market, technology and industry variables as a state-machine-like scheme where the variables are represented by nodes and their influence is represented by arrows. The detailed model presented by Pagani (2008) provides accurate results for short term forecasts. When referring to longer term forecast we need to simplify the description at the cost of reduced accuracy. Following the principles presented by Pagani (2008), we describe the method of generating Table 5 and Table 6 data as a state-machine flow. The diffusion process is influenced by the following factors: the attributes, price premium and availability, sales of each hybrid category and battery cost. Each factor influences the other factors according to Eqs. (6-1)-(6-8). Starting with some initial conditions, detailed in the first rows of Table 5 and Table 6, we can proceed by calculating the results of iterations according to Eqs. (6-1)-(6-8). The results of every iteration serve as initial conditions for the next one. At each iteration we add a row in Table 5 and Table 6. The state-machine is presented in Figure 12.

Figure 12: A Simplified Industry & Market Relations Chart



A graphic description of market dynamics forecasting is shown in Table 6 and Figure 13. The chart shows not only the transition of the market to hybrid and electric, but also the substitution between generations. The price premium forecast (see Table 5 and Figure 14), availability forecast (see Table 5 and Figure 15) and battery cost forecast (see Table 5 and Figure 16) are also the results of the iterations.

Table 5 shows the evolution path of the attributes resulting from our model. In Table 5 we marked the initial data, based on manufacturers' announced plans, in ***italic bold***. The premium price of the HEV0 in the years 2008 and 2009 is higher than expected, since battery costs in a competitive market are considered, where there is little competition. As more car manufacturers join the hybrid trend prices will adjust and reflect the declining cost of batteries.

In Table 6 we marked the initial actual sales data, from market statistics sources, in ***italic bold***. The sales forecast of the BEV is based on pre-orders (in the years 2008 and 2009), and on market surveys for specific niches until 2013.

Figure 13: Hybrid Adoption Forecasting

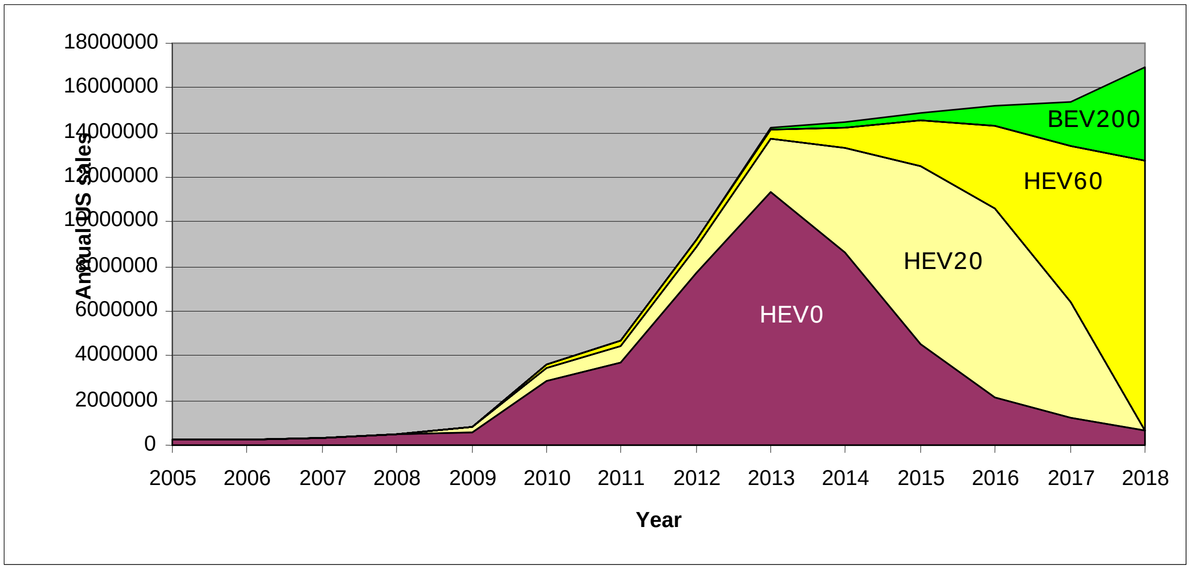


Figure 14: Price Premium ($) Evolution Forecast

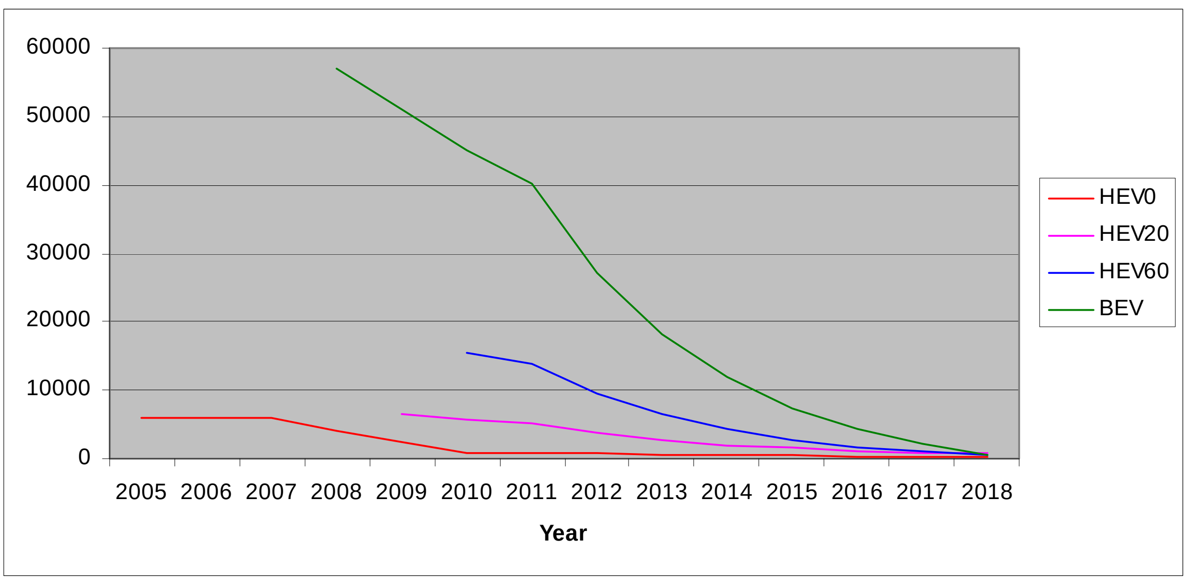


Figure 15: Hybrids Availability Forecast

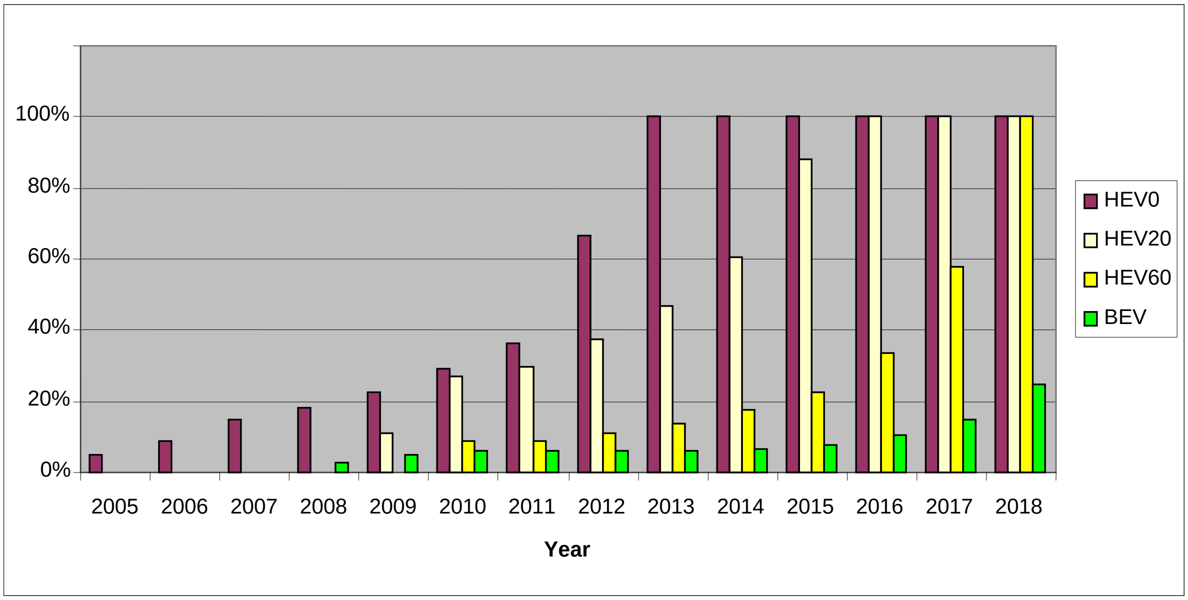
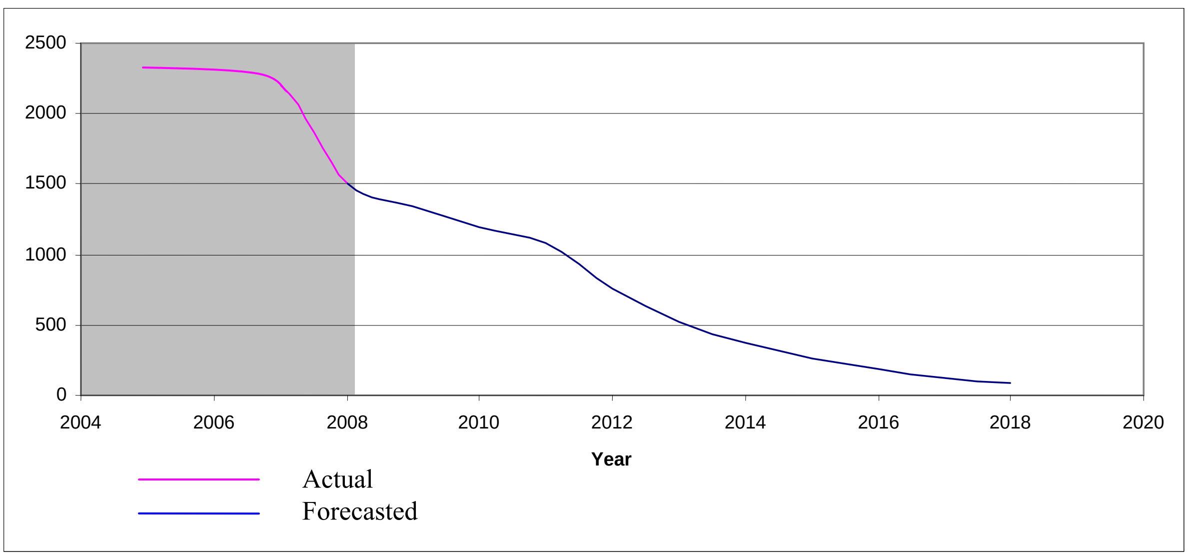


Figure 16: Battery Cost ($/KWHr) Forecast



6.2.8 Repurchase of Hybrids

Unlike many other products, cars change ownership several times before they are disposed of. New cars are purchased by a sub-group of adopters and traded in after several years to other segments. Trade-in agencies offer convenient arrangements for upgrading a car both for new and used car buyers. We refer to trade-in as a role exchange where an existing adopter transfers his status of an actual adopter to another customer while he/she becomes a new adopter again. This market characteristic has an effect on car manufacturers, who target[52] the segment of new cars buyers, but does not influence the overall market acceptance. The market can be viewed as a queue where new cars are delivered to a certain segment of customers who buy new cars and then transfer them along the queue, through trade-in, until the cars are disposed of. Repurchase, or upgrading a car, is counted when an old car is disposed of and a new car replaces it, not necessarily at the hands of the same person. The high costs of replacing a car cause repurchase due to obsolescence to be uncommon. The common case is that a customer replaces his/her car by a new one when it wears out and does not provide the same comfort as a new car.

The average lifetime of a car, given the total number of US registered cars and the number of cars purchased every year and given that the US car market is nearly stable, is, see Eq. (6-1), $T = \alpha^{-1} = \frac{241}{17} \approx 14$ years. We assume that the same lifetime will be maintained for hybrids as well, although the lifetime of hybrids is expected to be slightly longer due to superior reliability, robustness and durability of the electric power train relative to internal combustion. In order to estimate repurchase we need to estimate the number of cars that will be disposed of. We can use the simplistic regulated lifetime formula, as in Eq. (5-4), or assume some statistic distribution of the lifetime using Eq. (5-7). For both options, we need to estimate the share of the repurchase sales that would be allocated to each hybrid category. Owners of early hybrids may switch to a more advanced hybrid category, due to improvements in attributes. Thus, repurchase at time *t*, $r^{w}(t)$, is a vector where each component refers to a different hybrid car type.

Disposal of a vehicle can stem from physical wear-out of the vehicle, when owners decide that the value provided by the car is less than its maintenance costs and it cannot be traded, or due to regulations that prohibit possessing old cars. Disposal costs, of crushing or other methods, may also influence practical lifetime. Strict regulation and relatively high disposal costs may cause the majority of owners to dispose of the car when it reaches a certain age with a little variance. When lifetime is

[52] Car marketers do care about the traded car market because new cars buyers need to sell their old one to partly finance a new one.

not regulated it is likely to have some statistic distribution, for example Rayleigh, see Olson and Choi (1985) or truncated normal, see Kamakura and Balasubramanian (1987), and some owners may keep their old car for a long time.

We forecast the hybrid market using both options. We present market dynamics assuming two lifetime options:

(a) Rayleigh distribution lifetime with average lifetime *E(T)=14* and $\sigma = 11.2$, using Eq. (5-7)

(b) Regulated lifetime, using the regulated model, Eq. (5-4) with *T=14*.

The replacement at time *t*, based on assumption (a), using Eqs. (4-5), (4-7), (5-7) and (6-2b), is:

$$\begin{pmatrix} r_1^w(t) \\ r_2^w(t) \\ r_3^w(t) \\ r_4^w(t) \end{pmatrix} = \frac{\sum_{i=1}^{4}\sum_{\tau=0}^{t-1} s_i^w(\tau)\cdot\left(e^{-\frac{(t-\tau-1)^2}{2\cdot\sigma^2}} - e^{-\frac{(t-\tau)^2}{2\cdot\sigma^2}}\right)}{\tilde{\tilde{m}}_4(A_{1,4},A_{2,4})}\cdot\begin{pmatrix} \tilde{\tilde{m}}_1(A_{1,1},A_{2,1}) - \tilde{\tilde{m}}_2(A_{1,2},A_{2,2}) \\ \tilde{\tilde{m}}_2(A_{1,2},A_{2,2}) - \tilde{\tilde{m}}_3(A_{1,3},A_{2,3}) \\ \tilde{\tilde{m}}_3(A_{1,3},A_{2,3)}) - \tilde{\tilde{m}}_4(A_{1,4},A_{2,4}) \\ \tilde{\tilde{m}}_4(A_{1,4},A_{2,4}) \end{pmatrix};\ \sigma = 11.2.\ \text{(6-10a)}$$

Note that $\sum_{i=1}^{4}\sum_{\tau=0}^{t-1} s_i^w(\tau)\cdot\left(e^{-\frac{(t-\tau-1)^2}{2\cdot\sigma^2}} - e^{-\frac{(t-\tau)^2}{2\cdot\sigma^2}}\right)$ is the disposals of all hybrid types at time *t* and $\tilde{\tilde{m}}_4(A_{1,4},A_{2,4})$ is the sum of the market shares of all hybrid types.

The replacement at time *t*, based on assumption (b), using Eqs. (4-5), (4-7), (5-5) and (6-2b), is:

$$\begin{pmatrix} r_1^w(t) \\ r_2^w(t) \\ r_3^w(t) \\ r_4^w(t) \end{pmatrix} = \frac{\sum_{i=1}^{4} s_i^w(t-T)}{\tilde{\tilde{m}}_4(A_{1,4},A_{2,4})}\cdot\begin{pmatrix} \tilde{\tilde{m}}_1(A_{1,1},A_{2,1}) - \tilde{\tilde{m}}_2(A_{1,2},A_{2,2}) \\ \tilde{\tilde{m}}_2(A_{1,2},A_{2,2}) - \tilde{\tilde{m}}_3(A_{1,3},A_{2,3}) \\ \tilde{\tilde{m}}_3(A_{1,3},A_{2,3)}) - \tilde{\tilde{m}}_4(A_{1,4},A_{2,4}) \\ \tilde{\tilde{m}}_4(A_{1,4},A_{2,4}) \end{pmatrix};\ T = 14.\ \text{(6-10b)}$$

Note that $\sum_{i=1}^{4} s_i^w(t-T)$ is the disposals of all hybrid types at time *t* and $\tilde{\tilde{m}}_4(A_{1,4},A_{2,4})$ is the sum of the market shares of all hybrids' types.

In the next section we will generate the forecasts, using options (a) and (b), and compare the results.

6.2.9 Forecasting of Sales, Adoption and Repurchase, of Hybrids

The influence of repurchase, at the beginning of market growth, is insignificant. As noted by Steffens (2002), when the market starts to mature, replacement takes a growing share of overall sales. As noted above, due to their high costs for cars we refer only to repurchase due to wear-out. Based on Eqs. (6-1) and (6-3a), a car in the US is disposed of after fourteen years in service on average. This means that hybrid repurchase will start to influence sales' volumes after 2017. At that time customers who replace any type of hybrid will probably choose the more advanced categories since, at that time, they would have a technological advantage over the alternatives. Other customers, the late adopters, will switch from conventional cars to hybrids at that time. The cumulative market share of early hybrids will decline due to attrition since customers of early hybrids will switch to advanced ones.

Overall sales are calculated using Eq. (4-4) as the sum, adoption and repurchase due to wear out. Adoption is calculated using Eq. (4-6) and the parameters from Eqs. (6-1)-(6-10b). For calculating the number of actual users, or the number of registered hybrid cars, we consider disposals which are subtracted from adoption level. In models that refer to a single product, such as that of Olson and Choi (1985), disposals are compensated by repeat purchase. In our case, since we refer to several hybrid categories simultaneously, disposals of early hybrids are likely to be replaced by advance generations leading to a decline in the number of old hybrids and an increase in the number of advanced hybrids.

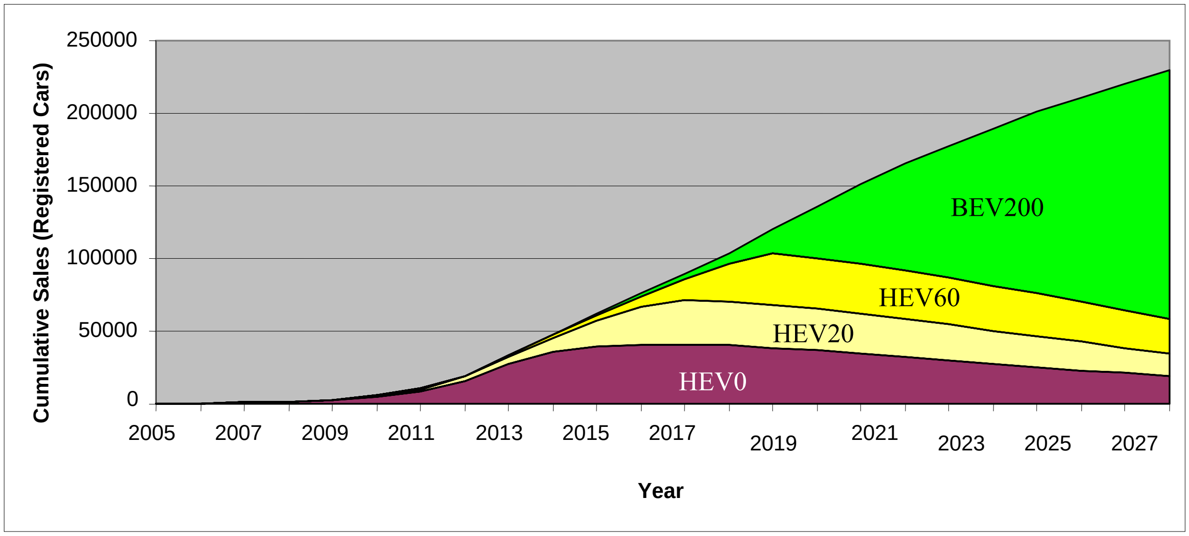
The US hybrid market development of both aspects, adoption and repeat purchase, is detailed in Table 7. The numbers are given in thousands of units sold. At this forecast we use assumption (a) of a Rayleigh distributed lifetime. A graphic representation of market development, including the relative share of each hybrid category is show in Figure 17. The numbers are given in thousands of vehicles shipped.

Table 7: Adoption, Disposals and Repeat Purchase Forecast with Rayleigh Lifetime

	New Adoption (in thousands)				Disposals (in thousands)				Repeat Purchase (in thousands)			
Year	**HEV0**	**HEV20**	**HEV60**	**BEV**	**HEV0**	**HEV20**	**HEV60**	**BEV**	**HEV0**	**HEV20**	**HEV60**	**BEV**
2005	206	0	0	0	0	0	0	0	0	0	0	0
2006	247	0	0	0	1	0	0	0	0	0	0	0
2007	353	0	0	0	3	0	0	0	0	0	0	0
2008	529	0	0	0	8	0	0	0	0	0	0	0
2009	549	292	0	2	17	0	0	0	0	0	0	0
2010	2842	629	182	5	29	1	0	0	0	0	0	0
2011	3696	765	214	8	54	6	1	0	0	0	0	0
2012	7718	1128	331	29	103	16	3	0	0	0	0	0
2013	11333	2381	408	135	196	33	7	0	0	0	0	0
2014	8646	4646	941	220	360	64	15	1	0	0	0	0
2015	4547	7909	2124	336	595	121	27	3	0	0	0	0
2016	2099	8501	3676	907	869	225	50	8	0	0	0	0
2017	1268	5140	6957	2033	1150	389	96	17	0	0	0	0
2018	698	0	12057	4187	1419	599	182	37	0	0	0	0
2019	303	0	7867	7976	1664	815	339	82	62	0	1470	1368
2020	28	0	459	15476	1878	1013	573	178	7	0	114	3522
2021	0	0	0	14878	2055	1189	834	383	0	0	0	4461
2022	0	0	0	13822	2192	1339	1078	731	0	0	0	5341
2023	0	0	0	12842	2288	1462	1298	1216	0	0	0	6264
2024	0	0	0	11931	2343	1555	1490	1825	0	0	0	7213
2025	0	0	0	11084	2359	1619	1650	2544	0	0	0	8173
2026	0	0	0	10298	2339	1654	1777	3359	0	0	0	9130
2027	0	0	0	9567	2287	1662	1869	4254	0	0	0	10072
2028	0	0	0	8888	2206	1644	1927	5211	0	0	0	10989

Figure 17 presents the market dynamics, including generations' substitution, for the next two decades, assuming a Rayleigh distribution of the lifetime. The cumulative market acceptance is calculated as the sum of new adoption and repurchase minus disposals for each hybrid category. The forecast is that the market will shift toward advanced hybrids but all hybrid categories will co-exist for a long time.

Figure 17: Hybrids Cumulative Market Acceptance with Rayleigh Lifetime



If we use assumption (b) of a regulated lifetime, as did Lawrence and Lawton (1981), rather than of statistically distributed one, the general trend remains, but there is an influence on market behavior. The market development of new adoption and repeat purchase, under the regulated lifetime assumption, is detailed in Table 8.

Figure 18: Hybrid Cumulative Market Acceptance with Regulated Lifetime

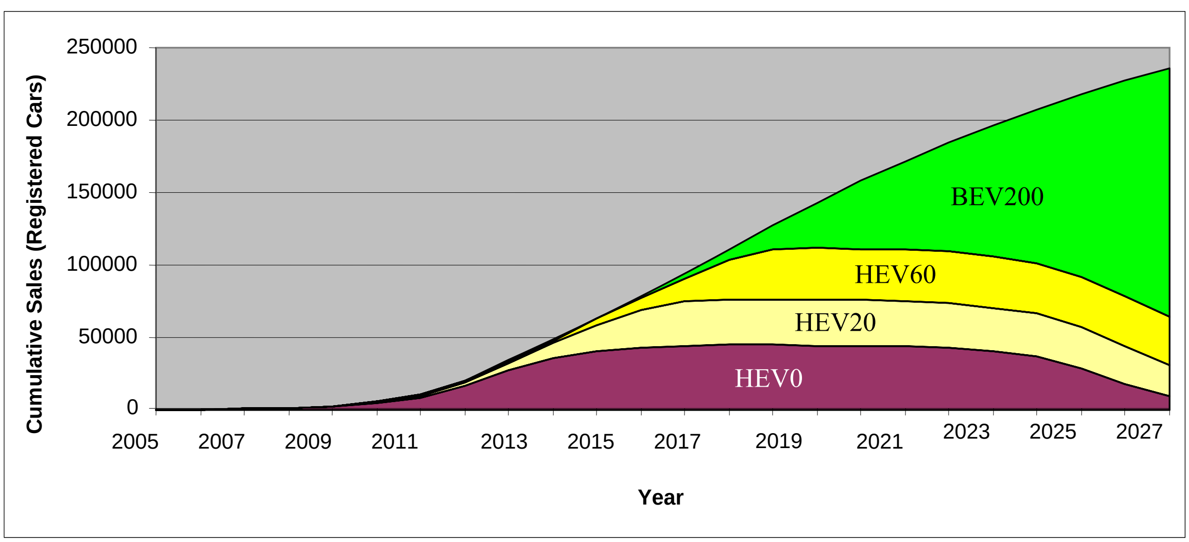


Table 8: Adoption, Disposals and Repeat Purchase Forecast with Regulated Lifetime

	New Adoption				Disposals				Repeat Purchase			
Year	**HEV0**	**HEV20**	**HEV60**	**BEV**	**HEV0**	**HEV20**	**HEV60**	**BEV**	**HEV0**	**HEV20**	**HEV60**	**BEV**
2005	206	0	0	0	0	0	0	0	0	0	0	0
2006	247	0	0	0	0	0	0	0	0	0	0	0
2007	353	0	0	0	0	0	0	0	0	0	0	0
2008	529	0	0	0	0	0	0	0	0	0	0	0
2009	549	292	0	2	0	0	0	0	0	0	0	0
2010	2842	629	182	5	0	0	0	0	0	0	0	0
2011	3696	765	214	8	0	0	0	0	0	0	0	0
2012	7718	1128	331	29	0	0	0	0	0	0	0	0
2013	11333	2381	408	135	0	0	0	0	0	0	0	0
2014	8646	4646	941	220	0	0	0	0	0	0	0	0
2015	4547	7909	2124	336	0	0	0	0	0	0	0	0
2016	2099	8501	3676	907	0	0	0	0	0	0	0	0
2017	1268	5140	6957	2033	0	0	0	0	0	0	0	0
2018	698	0	12057	4187	0	0	0	0	0	0	0	0
2019	303	0	7867	7976	206	0	0	0	4	0	104	97
2020	28	0	459	15476	247	0	0	0	0	0	8	239
2021	0	0	0	14878	353	0	0	0	0	0	0	353
2022	0	0	0	13822	529	0	0	0	0	0	0	529
2023	0	0	0	12842	549	292	0	2	0	0	0	842
2024	0	0	0	11931	2842	629	182	5	0	0	0	3657
2025	0	0	0	11084	3696	765	214	8	0	0	0	4682
2026	0	0	0	10298	7718	1128	331	29	0	0	0	9207
2027	0	0	0	9567	11333	2381	408	135	0	0	0	14258
2028	0	0	0	8888	8646	4646	941	220	0	0	0	14453

Figure 18 presents the market dynamics, including generations' substitution for the next two decades, assuming a regulated distribution of the lifetime. Considering the accuracy expected from such a long term forecast, we can say that the difference between the forecasts, with two different lifetime characteristics, is insignificant.

6.2.10 Accuracy Assessment

Benchmarking our forecast against a forecast reference or actual sales is avoided since no actual sales data or reliable sales forecasts are available today. Furthermore, forecasting generations' substitution of future generations is a contribution of our model and cannot be compared to the forecasts of other diffusion models. To benchmark our forecast against actual sales data we will need to wait several years. To provide a measure for the robustness of our forecast we describe the impact of variations of the model parameters on the forecast outcome. We can also run a sensitivity analysis, used in operations research, for finding certain connections. For example we can calculate the sensitivity of the hybrid premium to variations in the battery cost reduction rate using Eqs. (6-4), (6-6a) and (6-6b). Similarly, we can calculate the sensitivity of the availability to variations in the car model development cost using Eq. (6-8). Such measures can provide the sensitivity and parameters range at any required time[53]. In our case, since we are interested in the overall trend, we demonstrate how certain parameter variations impact the forecast. The same method can be applied to any of our model parameters. We applied the method for the adoption phase since at the repurchase forecast we already included the impact of a variation of the lifetime.

We performed a sensitivity analysis to check the changes in the forecast as a function of a variation of the parameters or some modification of the assumptions related to the car industry and market. For the demand side we take the variations ranges, which are quite modest, and confidence from Graham (2001). For the supply side we take much higher variations. In our model the forecast of each hybrid type is tightly related to changes in other hybrid types. We take the forecast parameters and results presented above as a reference and calculate the RMSE of the differences between the forecast with a modified parameter and the reference forecast as a measure for the sensitivity of the forecast to that parameter. We measure the RMSE, of the sales in car numbers, for each hybrid type separately. The variations and sensitivity are summarized in Table 9.

Table 9: Sensitivity of Forecasted Sales to Parameters Variations (RMSE)

Category	Parameter and variation	HEV0	HEV20	HEV60	BEV200
Demand as a function of attributes[54]	HEV0 demand is lower by 3%	288519	10872	8980	6924
	HEV0 demand is larger by 3%	286681	10817	8933	6897
	HEV20 demand is lower by 3%	237331	232678	0	0
	HEV20 demand is larger by 3%	244235	236607	0	0
	HEV60 demand is lower by 3%	19126	168973	177329	41988
	HEV60 demand is larger by 3%	19251	177407	163934	42706
Battery cost reduction rate limit	25% (rather than 30%)	699905	857146	825877	644659
	20% (rather than 30%)	1372673	1670259	1832144	1056931
	15% (rather than 30%)	2223288	2246395	2774842	1138286
Car development cost	80 million (rather than 90 million)	487685	509685	434896	153607
	100 million (rather than 90 million)	369021	465277	566444	116068
Simplifying assumption	Calculate revenues by accurate car price rather than $20,000 per car	361872	767731	753363	369313

The RMSE at Table 9 are modest, relative to an annual market of 17,000,000. Detailed information about parameters variations range and impact is provided in Appendix D.

[53] For the hybrid case we refer to 19 parameters and 14 time points so there are 14x19=261 ranges.
[54] Graham (2001) provides the confidence intervals of HEV0, HEV20 and HEV60, which are $\pm 3.1\%$, $\pm 2.8\%$ and $\pm 2.3\%$, correspondingly. See Graham (2001) section 5.2.4.1.