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Return on Investment Analysis for Implementing Barriers to Reverse Engineering and Imitation

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ABSTRACT

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Reverse Engineering and Imitation

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Reverse engineering (extracting information about a product from the product itself) is a competitive strategy for many firms and is often costly to innovators. Recent research has proven metrics for estimating the reverse engineering time and barrier and has shown that products can strategically be made more difficult to reverse engineer, thus protecting the innovator. Reverse engineering, however, is only the first phase of attempting to duplicate a product. Imitating – the process of discovering how to physically reproduce the performance of the reverse engineered product in one or more of its performance areas – is the second and final phase. This thesis presents metrics for the time and barrier to imitating and shows how they can be joined with reverse engineering metrics to estimate a total time and total barrier to duplicate a product. As there is a cost associated with the design of barriers to reverse engineering and in imitating it is important that a return on investment analysis be performed to ensure a profitable endeavor. Details of such an analysis are presented here. To illustrate the methodology, two case studies are presented. The first is an analysis of KithcenAid's Stand Mixer. The second is an analysis of a cantilevered "L-beam" that has been structurally optimized under four conditions to achieve a specified mechanical performance. Additionally, anecdotal solutions to creating barriers to reverse engineering and imitating are discussed throughout.

Keywords: imitate, reverse engineer, barrier to reverse engineer, barrier to imitate, return on investment, product design, product development

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NOMENCLATURE

B	Barrier to extract information during reverse engineering or imitating
C	Costs related to a product
F	The rate of information extraction during reverse engineering or imitating
K	Quantity or units of information
n	Bass Diffusion Model sales probability density function
m	Estimated market size in number of units
P	Fraction of power exerted to extract information
Q	Return on investment ratio
r	Product revenue
S	The ability of a product to store information as it relates to reverse engineering or imitating
X	The dollar sales of a product
T	Total time to extract information from a product (during reverse engineering or imitating)
α	Bass Diffusion Model coefficient of early adoption
β	Bass Diffusion Model coefficient of late adoption
δ	The end deflection of a cantilevered L-beam
Ψ	The sales volume of a product
ρ	Product retail price
τ	Time

Subscripts, superscripts, and other indicators

$[\ ]_0$	Indicates the initial value for [ ]
$[\ ]_c$	Indicates [ ] pertains to a competitor
$[\ ]_d$	Indicates [ ] pertains to product development
$[\ ]_f$	Indicates [ ] is evaluated at the end of product life
$[\ ]_g$	Indicates [ ] pertains to goods sold
$[\ ]_I$	Indicates [ ] pertains to imitating
$[\ ]_m$	Indicates [ ] pertains to manufacturing
$[\ ]_M$	Indicates [ ] pertains to market entry
$[\ ]_R$	Indicates [ ] pertains to reverse engineering
$[\ ]_t$	Indicates [ ] pertains to a total value
$[\ ]_u$	Indicates [ ] occurs at the upper limit of sales
$[\ ]^*$	Indicates [ ] pertains to a total value

CHAPTER 1. INTRODUCTION

1.1 Background

Preeminent design and manufacturing industries rely on advanced research and development activities to design products or systems that have competitive advantages in the market place. Unfortunately, the advantages gained are often lost when dominant products are reverse engineered and then imitated by competitors. Competitors often pursue imitating to (i) reduce development costs and (ii) quickly enter a market [2–6]. Shapiro [7] and Nelson and Winter [8] emphasize that the harder it is to imitate a product the less incentive there is for competitors to imitate the product. Therefore, strategic design approaches that increase the difficulty to imitate a product are worth developing. This thesis presents the development of one such approach. For clarity of presentation, three critical definitions are provided:

Reverse Engineering is the process of extracting information about an product from the product itself. A *Barrier to Reverse Engineering*, therefore, is anything that impedes that extraction of information [9].

Imitation is the process of discovering how to physically reproduce the performance of the reverse engineered product in one or more of its performance areas. Additionally, a *Barrier to Imitation* is anything that keeps the reverse engineered product from being adequately reproduced.

Market Entry of a competitor releasing an imitation product can occur only after the process of reverse engineering and imitating. Therefore, a *Barrier to Market Entry* is a function of both the reverse engineering and imitation barriers.

Product imitating happens in many different markets. From military to consumer electronics, there are examples where imitation has had a significant impact on the market [10, 11]. The release of an imitation product to the masses often competes directly with and can decrease the sales of the original product [12]. In 2003 Chevrolet released a compact, five person vehicle in China called the Spark. Shortly after, Chery, a Chinese auto maker, released the QQ, which was less expensive than the Spark. The QQ resembled the Spark to such a degree that critical components could be interchanged on the two. In 2004, the QQ outsold the spark nearly five to one [13]. Because imitating can decrease development costs, imitators are often able to reduce the retail cost, and have a greater potential of outselling the original product [14, 15].

When a designer releases an innovative product to the market, he/she is intent on maintaining a competitive advantage by protecting details regarding the enabling technology. To imitate the enabling technology of a product, competitors often try to expose that technology through *reverse engineering*. Reverse engineering difficulty is dependent on the quantity and type of information contained in the artifact. Some information types, such as linear dimensions, are easier to extract than other types of information, including material properties. Harston and Mattson [16] present metrics for the barrier and time for reverse engineering. With their metrics and knowing the quantity and types of information that are contained in a product, the barrier to reverse engineering can be calculated. From the barrier, the time to reverse engineer a product can be estimated. The metrics presented by Harston and Mattson are particulary useful during product development when designers are free to add features that increase a product's resistance to reverse engineering and imitating; the metrics can be useful to quantify the effectiveness of one feature versus another.

Along with diminishing competitive advantage and capturing market share from the innovator, imitations reduce the return on investment for the innovator [5, 17]. Patents are one way to secure intellectual property. The downfall of patents, however, is that they disclose the enabling technology of a product and aid imitators in avoiding patent infringement while maintaining comparable performance [4]. Gruca and Sudharshan [12] propose a framework for deterring competitors from entering the market. Their framework is based on business strategies that can range from single elements of the marketing mix to overall corporate strategy. Porter provides measures that help a company structure its strategy so it can maintain a competitive advantage [18]. Those strategies can range from being a low cost provider to being at the forefront of technology. Part of Porter's model calls for analyzing the possibility of a competitor imitating a product. These are just a couple examples of how an anti barrier business strategy can help to maintain competitive advantage.

Researchers have expressed, from various perspectives, the need to estimate and quantify the time and barrier to imitate a product [19–21]. Macmillan et al. [22], state that knowing competitors' response lag (or time to imitate) is essential to understanding the financial risk involved with developing a new product. Further, Pahl et al. [23] insist that understanding a product's life-cycle and competitors' products (or ability to produce products) is fundamental to effective product planning. This thesis addresses these issues by illustrating how an innovator's return on investment can be increased through an understanding of competitors' response lag and effective product planning.

The concept of barriers to reverse engineering and imitating is a valuable concept, and one that has its greatest pragmatic impact when it creates a larger return on investment than any alternative. The return on investment, in general, is dependent on the costs for development and sustaining, as well as the revenues generated, and is calculated as the ratio of the two. The revenues generated can be negatively impacted by the entrance of a competitor into the market. How great the impact is depends on many factors, but the factor that is of most interest here is the time at which the competitor enters the market [24]. Generally, an early entrance has a greater negative impact on the original developer than a later entrance. Therefore, the innovator prefers that an imitator's market entry point is delayed as long as possible. A calculated optimal delay requiring minimal additional design effort by the innovator is the sought scenario.

Actually developing and releasing a product to market is not within the scope of this thesis. Therefore, it is not possible to fully test and validate new theories. However, it is possible to use industry proven models to build a framework for evaluating the return on investment for implementing barriers to reverse engineering and imitation. This thesis combines three proven theories to provide one analysis of return on investment. Specifically, the theories are barriers to reverse engineering [9], the flow rate of extracting information [25], and the market diffusion of new products [26]. Used alone, these theories have little value in making barrier implementation decisions. The framework outlined in this thesis brings greater value to these theories by analyzing them conjointly to evaluate return on investment, which is the recommended metric for making barrier based design decisions.

In order facilitate the integration of the three theories mentioned above, three new developments are needed: (i) an extrapolation of the barriers to reverse engineering theory to a barriers to imitation theory, (ii) the manipulation of the market diffusion theory to account for the market entry of a competitor, and (iii) a final return on investment metric that includes elements of barriers to reverse engineering, barriers to imitation, and the market diffusion model.

1.2 Technical Preliminaries

In this section the foundation is laid for the theories and case studies that will be presented in this thesis. The metrics developed by Harston and Mattson are discussed. An enabling technology to building difficult to overcome reverse engineering and imitating barriers, ultrasonic consolidation, is explained. Also, recommendations are made about how one can utilize ultrasonic consolidation to build barriers into a product.

1.2.1 Reverse Engineering Metrics

Reverse engineering is only the first phase in attempting to imitate a product. Imitating is the second and final phase. Therefore, the metrics developed by Harston and Mattson must be considered in a broader sense to be of most use. In Section 2.2, it is explained how these same metrics can be extended to predict the time and barrier to imitating. Before proceeding however, a discussion of published reverse engineering metrics is necessary.

Using the basic principles of Ohm's Law [27], Harston and Mattson define the quantitative barrier to reverse engineer a product as

$$B_R = \frac{P_R}{F_R^2} \tag{1.1}$$

where P_R is the power (effort) exerted per time to extract information, and F_R (flow rate) is the rate at which information is extracted from the product. F_R is generally dependant on three factors: information complexity, skills of the team, and available resources. P_R is constrained by

$$0 < P_R \leq 1 \tag{1.2}$$

where “0” represents no effort put forth to reverse engineer and “1” represents the maximum effort one can put forth to reverse engineer. The R subscript is present to distinguish these as being for reverse engineering. Noting Equation (1.1), the reverse engineering barrier will increase as the flow rate decreases with power being held constant. If flow rate is held constant and power is free to increase, then the barrier increases, signifying that more effort is required to reverse engineer the product. To the innovator trying to protect his or her innovation, a conservative approach is

$$P_R = 1 \tag{1.3}$$

Just like a capacitor in an electrical circuit, a product has a storage ability. Instead of storing electricity, like a capacitor, the product stores information. The storage capacity, S_R, of a product is defined as

$$S_R = \frac{K_R F_R}{P_R} \tag{1.4}$$

where K_R is the amount of information contained in the product that has not yet been extracted. With that, the parameters necessary to predict the time, T_R, required to reverse engineer a product are available, which is defined using an exponential decay

$$T_R = -B_R S_R \ln\left(\frac{K_R}{K_{R0}}\right) \tag{1.5}$$

where K_{R0} is the total initial amount of information stored by a product. Thus,

$$0 < K_R \leq K_{R0} \tag{1.6}$$

At this point it is important to note that information is separated by types and the preceding metrics are applied separately to each type of information. Therefore, if K_R, F_R, and P_R are known for a given information type, S_R, B_R, and T_R can be calculated for that information type.

Since products generally contain more than one type of information, it is important that T_R is calculated separately for each type of information. How information types are categorized is left up to the individual performing the analysis. However, F_R must be assigned appropriately to each information type. Methods for assigning values for F_R are outlined by Harston [9] and

Anderson [25] and are also discussed below. In order to obtain total product reverse engineering time (T_R^*), the time to reverse engineer every type of information must first be calculated. T_R^* is then calculated by summing the individual times. The effective information flow rate for all information contained by the product is calculated by

$$F_R^* = \frac{K_R^*}{T_R^*} \tag{1.7}$$

where K_R^* is the total information content of the product. From that, the effective power applied to reverse engineer the entire product is calculated as

$$P_R^* = \frac{K_R^* F_R^*}{T_R^*} \tag{1.8}$$

With F_R^* and P_R^* defined, the total quantitative barrier is

$$B_R^* = \frac{P_R^*}{F_R^{*2}} \tag{1.9}$$

It is beneficial to consider both B_R^* and T_R^* as reverse engineering measures, as they are related, yet distinctly different. It is possible for a product to have a small B_R^*, but a large T_R^* due to the amount of information contained by the product. For example, consider a large flat plate with numerous holes of various sizes throughout. The barrier to measure the diameter of any single hole is small. The time it takes to reverse engineer the entire product is relatively large due to the large amount of unique measurements that need to be made. Therefore, it is possible to have a small value for B_R^* and a large value for T_R^*.

1.2.2 Information Flow Rate Estimation

As mentioned above, F is a key component in evaluating T and B. Harston and Mattson [9] made a valuable observation in studying how long it takes an individual to reverse engineer a product. Their study presented a product to an individual and then separately recorded the time it took to extract each and every piece of information. They then reordered the times from shortest to longest. They discovered that, for sufficiently complex products, the total time it takes an individual to extract all of the information contained by a product can be estimated by an exponential relationship. For simpler products, the time to extract information is better predicted by a linear relationship. Figure 1.1 illustrates their findings. The linear prediction shown in Figure 1.1 illustrates the lower bound estimated time to reverse engineer a product.

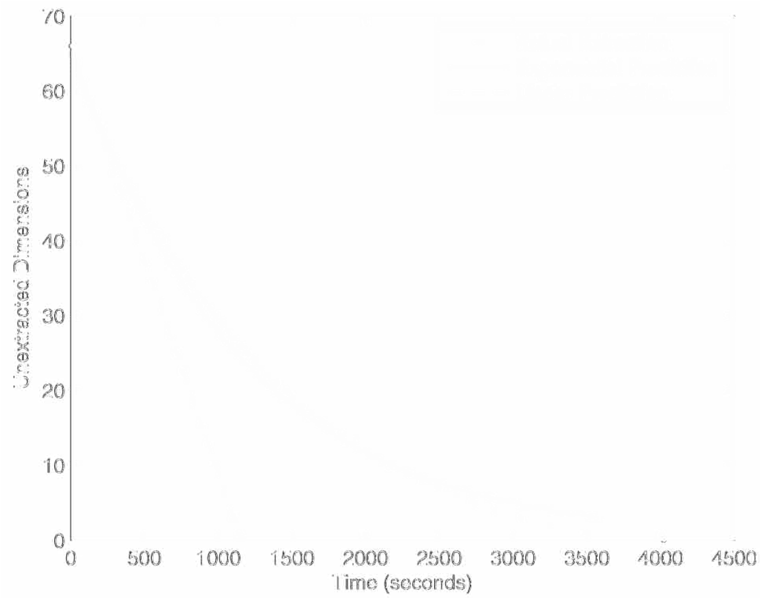

Figure 1.1: Example of estimated time to reverse engineer a product using a linear and exponential prediction.

Both the linear and exponential estimations are generated using only the slope between $Time = 0$ and the point representing the fastest information flow rate. How well an exponential relationship predicts the time it takes to reverse engineer a product is dependant on how complex the given product is. For the simplest products, the linear prediction may be more appropriate. Harston and Mattson's study was conducted only considering geometric information, which can be classified among the more simple types of product information. As more complex types of information (i.e., microstructure information) are incorporated into a product the exponential relationship will be the preferred evaluation method. Their study also revealed that the fastest flow rate only needs to be known in order to predict the time it takes an individual to reverse engineer a product. For geometric dimensions, a typical flow rate is found to be approximately 0.04 dimensions per second [25]. Therefore, knowing the time it takes a competitor to reverse engineer and imitate a product will help innovators predict during which phase of the product life-cycle a competitor will launch an imitation.

1.2.3 The Product Life-Cycle

As Section 1.1 explains, the release of an imitation has an adverse affect on the innovator's return on investment. Barriers to reverse engineering and imitating are a vehicle, though, to deter or delay the release of an imitation. Thus, barriers to reverse engineering and imitating can aid an innovator in achieving a more desirable return on investment. Implementing barriers can be costly. Therefore, predicting how a given barrier will affect an innovator's return on investment is an essential step in deciding what barriers to implement. The life-cycle of a product is a key element in predicting the return on investment of a product. Understanding the time line of the product life-cycle will help developers better predict a product's return on investment. A typical product life-cycle consists of five basic phases (i) Development, (ii) Release, (iii) Growth, (iv) Maturation, and (v) Decline as illustrated by Figure 1.2 [23].

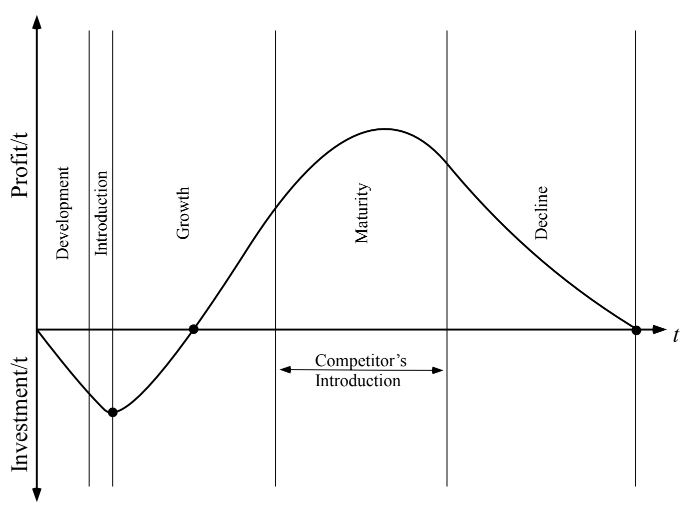

Figure 1.2: Example of a product's life-cycle based on the revenue generated and costs incurred (investment) during different stages of the product's life-cycle.

In the development phase, the form, fit, and function of a product is defined and implemented. The designer incurs the most debt during the development phase, as illustrated by the first downward trending line in the product life-cycle plot of Figure 1.2. In the introduction phase, the product's production is well under way and has been released to the masses. The designer still incurs increasing debt during the introduction phase, due to advertising, stocking distributors, and tooling, but it is for a relatively short time. The growth phase is where the designer begins gaining revenue, but his/her debt is still increasing until the break even point is reached. The break even point is the point in time that the designer is spending as much as he/she is generating in revenue, as indicated in Figure 1.2. Once the break even point as been exceeded the designer begins to recover his/her incurred debt. During the maturation phase the market reaches its saturation point. The market stays at its saturation point for a time and then begins to decline. The decline phase is where the market begins to die down and the product remains available to the masses until it is no longer profitable for the designer to leave that product on the market. It is important to note that the competitor's launch can occur during any stage. For the least impact at minimal development cost, it is ideal to have a competitor's launch close to or shortly after the market saturation point [28].

Extensive models have been developed to aid in predicting how the market, for a new product, will grow [26]. Additionally, other models have been developed that predict how a late entrant in the market will impact the market diffusion of the new product [28]. Before continuing, it is necessary to discuss an enabling technology to barrier creation and some of its applications and implications.

1.2.4 The Rotation and Lamination Theory

There are numerous ways that reverse engineering barriers and imitating barriers can be created. Some are more affective than others in delaying competitors from releasing an imitation. The barrier creation focus of this thesis is on creating barriers through materials design. The materials based design strategy for barrier creation pursued is based on creating designs that are sensitive to the manipulation of a material's microstructure. Material microstructure is defined as the composition of a material including arrangement, size, orientation and distribution density of crystallographic grains [29]. Xia and Wang [30] have proven that coupling geometric design with materials design can generate superior designs. For any given material there exists a finite range of possible material properties [29]. The values in that range are often obtained through manipulating the microstructure of the material by applying a strain or heat treatment. The bounds that enclose the space of obtainable material properties is called the *properties closure*.

Adams et al. [31] proposes a theory for accessing a greater range of material properties through rotation and lamination. This theory is realized through the use of ultrasonic consolidation (UC), an additive manufacturing process that uses ultrasonic vibration to weld thin metal foils together. Figure 1.3 illustrates the UC process and provides a scanning electron microscope image of the material grains at the weld interface of the metal foils. A rotating, ultrasonic oscillating sonotrode applies a normal force to the metal foil to break up the oxidation layer between the foil and the substrate, thus welding the two together. Note, that even under an electron microscope there are no noticeable voids in the weld interface. To the naked eye, it is very difficult to recognize a part that has been manufactured using UC. The implication is that UC can create a barrier that is extremely difficult and time consuming to uncover.

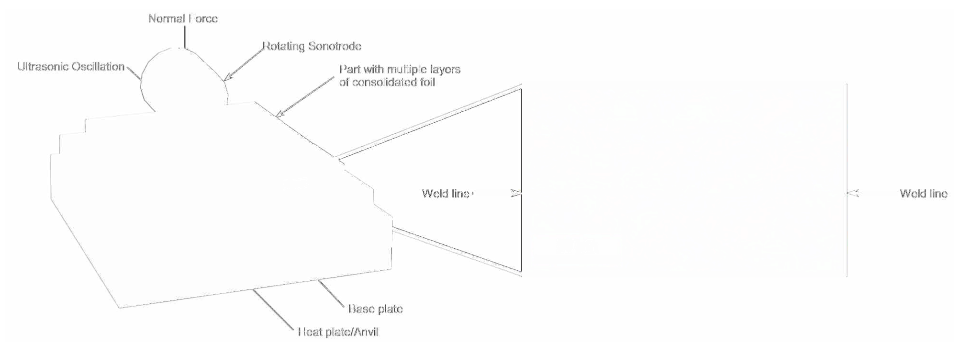

Figure 1.3: Illustration of the ultrasonic consolidation process as well as a scanning electron microscope image of the material grains at the layer weld interface.

The theory proposed by Adams et al. uses metal foils that are cut from an anisotropic material at a prescribed orientation, θ, as shown in Figure 1.4. Because the starting material is anisotropic the orientation at which the foils are cut out results in particular material properties along the longitudinal and lateral directions of the cutout. The metal foils can then be layered on top of each other, much like carbon fiber composites, using UC.

The advantage of UC is that there is negligible disturbance of the microstructure at the weld interface [32]. From observation and experience, trying to imitate a product that has been ultrasonically consolidated requires a specific set of skills to, figuratively speaking, peel away

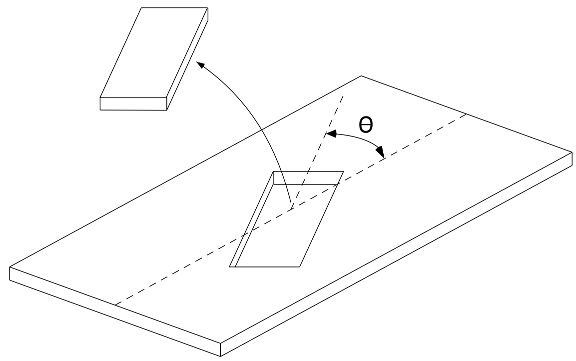

Figure 1.4: Example of a thin metal foil being cut from an anisotropic material at orientation θ, which can be used for ultrasonic consolidation.

the layers of information. Specifically, it requires a series of expensive and difficult scans using electron microscopy. This makes rotation and lamination a good barrier to imitation and a simple example of how to apply it to design is presented Section 3.2.

CHAPTER 2. NEW THEORETICAL DEVELOPMENTS

2.1 Barriers to Imitation

Just like reverse engineering, the key step in imitating is extracting information, though some of the information extraction in imitating is done through trial and error. With the information that has been gathered through reverse engineering, the imitator now has the task of gathering the information that allows the reverse engineering information to be replicated. For example, an imitator might know, from reverse engineering, what the material microstructure is of a given product. However, in order to imitate that product the imitator needs to know how to produce that microstructure. This means that the imitator needs to find a source that the material can be purchased from or determine how to manufacture it themselves. The information extraction phase of imitating can be much more time consuming and iterative than that of reverse engineering. For example, consider a piece of material that has undergone a series of strain inducing processes (i.e., cold working and heat treating) to achieve certain material properties. Figure 2.1 is a representation of a properties closure and shows how the material properties might change through a series of strain inducing processes. The path that is shown and must be followed to achieve the same material properties is referred to as the *strain path*. Through a variety of tests, someone trying to reverse engineer this mystery material will most likely be successful in determining the material properties. However, how to imitate (physically reproduce) that material is the more difficult and time consuming task, because of all the input parameters required for the various processes, such as heat treating. A conservative measure is to assume that the imitator chooses the correct heat treating parameters on the first attempt, but in reality it will take many iterations to determine the correct parameters. This is why information extraction in imitating is often done by trial and error. Further, the only indication that the imitator has that the correct strain path is being followed is that the material properties suddenly match those of the innovation. One can now see how the barrier and time to imitating rapidly grows as more points are added along the strain path. The implica-

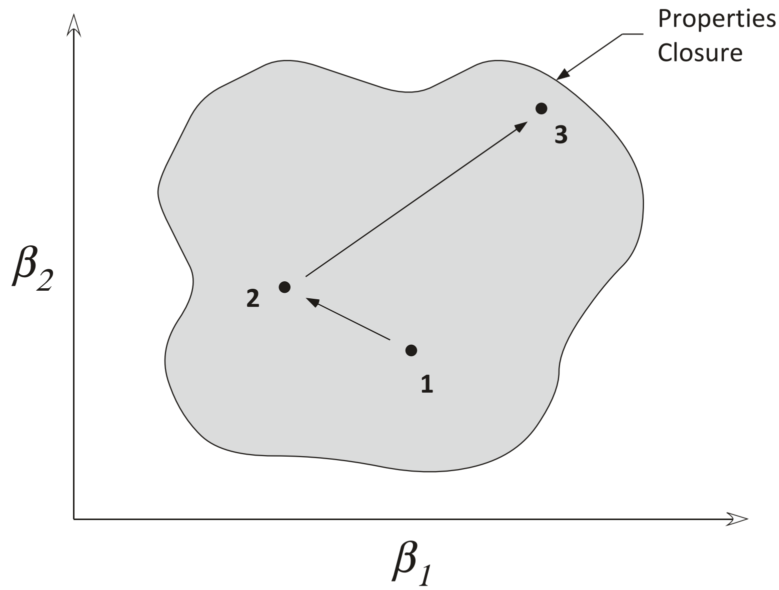

Figure 2.1: Properties closure for material properties β_1 and β_2. In order to reach point 3 from point 1, the material must first undergo a process to that passes through point 2.

tion is that barriers created through microstructure manipulation can be very effective in deterring imitators. Additionally, extracting the necessary imitating information can be much more time consuming than that for reverse engineering.

2.2 Barrier and Time Metrics for Imitating

As mention above, information extraction is a key step in both reverse engineering and imitating. During reverse engineering, all information is extracted from the product itself. During imitating, the information can come from two different sources: internal and external [33]. *Internal* information is that which can be obtained from the product itself. *External* information is that which is obtained from sources other than the product. Examples of external sources are experts in a given field, manufacturing process data, and published literature. Recall that when calculating the reverse engineering barrier and time, each information type is separately considered and analyzed. By definition, the reverse engineering barrier and time are only a function of internal information. On the other hand, a barrier to imitation is a function of both internal and external sources of information.

Calculating the reverse engineering time and barrier is based upon separating information into types; there is no limitation to how many types of information can exist within a product. It is important to note that how the information is grouped into types is up to the discretion of the designer. Since some imitating information is classified as internal, just like reverse engineering information is, it follows that information needed to imitate a product introduces additional *types* of information. Therefore, the reverse engineering metrics are easily extended to include the new information types. It now becomes a question of what is the appropriate F for each information type. The process outlined by Harston and Mattson for estimating the information flow rate of a competitor assumes that the fastest a competitor can extract information is no faster than the innovator. Therefore, a conservative estimate for the information flow rate, from the innovator's perspective, is to use the innovator's information flow rate. Adapted from Harston and Mattson, the equations for imitating are

$$B_I = \frac{P_I}{F_I^2} \tag{2.1}$$

$$S_I = \frac{K_I F_I}{P_I} \tag{2.2}$$

$$T_I = -B_I S_I \ln\left(\frac{K_I}{K_{I0}}\right) \tag{2.3}$$

$$0 < K_I \leq K_{I0} \tag{2.4}$$

The calculation of F^*, P^*, and B^* is performed as shown in Equations (1.7), (1.8), (1.9).

Though it is possible for them to occur in parallel, for this thesis it is assumed that reverse engineering and imitating are activities that can only occur in series. With that assumption, the fastest total time it takes for someone to reverse engineer, imitate, and release the imitation is the *time to market entry* and is defined as

$$T_M^* = T_R^* + T_I^* \tag{2.5}$$

and it is assumed that the imitator is not able to release an imitation any sooner than T_M^*.

The barriers to imitation metrics are a necessary piece in the development of the return on investment model presented in this thesis. Without these metrics, the estimation of the time to a competitor's market entry would have little value. Though the development of the barriers to imitation metrics is an extrapolation from the barriers to reverse engineering metrics, it is necessary. Fully developed barriers to imitation metrics would be costly for the scope of this research, yet the research could not move forward without this fundamental piece. Since imitation information is just additional types of information, this extrapolation is a reasonable one.

2.2.1 Flow Rate Estimation for Imitating

As implied above estimating F can be a simple process. A conservative measure is to assume a competitor's information flow rate is no faster than the innovator's flow rate. The estimation of F is simplified even further by only considering the simplest piece of information contained by a product. Anderson [25] states that the simplest geometric product, or geometric information, is a parallel pipet (cuboid). She calculated F by timing how long it takes to measure all three dimensions of the cuboid, dividing by three and using the reciprocal of its value. Based on the study done by Harston and Mattson and discussed in Section 1.2.2, the time to extract information from a product is no less than the linear prediction and no greater than the exponential prediction. Remember, how well the exponential relationship predicts overall information time is dependant on product information complexity. Considering *imitating* information adds complexity to any set of information, thus increasing the accuracy of the exponential relationship. Fortunately, the exponential prediction can be evaluated by only knowing the fastest information flow rate of each set of information type. It is logical to assume that the fastest information flow rate corresponds with the simplest piece of information and vice versa. Therefore, only two values are needed to estimate the total information extraction time: the flow rate associated with the simplest piece of information contained by the product and the total quantity of reverse engineering and imitating information necessary to replicate the product.

2.3 Return on Investment

With a foundation laid, it is now possible to further discuss how the return on investment of a product is influenced over its entire life-cycle. The business strategy behind implementing barriers to reverse engineering is two fold. The first is to protect innovator trade secrets. The second objective is for the innovator to capture and maintain a large majority of the market share for as long as possible. Maintaining a large market share helps increase return on investment (Q). There are two key components to estimating Q. The first is an estimation of all the costs associated with the product's development and production. The second is an estimation of the sales and market performance of the product. This section will explore how, with given models, a firm can estimate the sales and costs of its product. In the past, most designers have been far removed from financial estimations [34]. The development of concurrent engineering has drawn designers closer to the estimation of financials for a project and helped them make better design decisions. The purpose here is not to prescribe estimation models, but to show how given models can be applied to help designers make better barrier implementation decisions based on Q.

2.3.1 Product Development Costs

There are a variety of methods for estimating project costs and how those costs will be distributed over time. The method used is usually determined by the firm developing the product. Product complexity can be a major factor in determining product development costs. At the onset of a project, it can be difficult to get an estimate of the product development costs. Ulrich and Eppinger [35] provide some direction. They state that the costs associated with the product can be separated into four categories: development, ramp-up, marketing and support, and production. Development costs include all design, testing, and refinement costs up to production. Magrab [36] outlines several models for determining the development costs. Magrab states that the product's total cost is computed as

$$C_p = N_p(M+L+R)+T_0+S+D \tag{2.6}$$

where N_P is the lifetime product volume, M is the material cost per unit, L is the manufacturing labor per unit, R is the production resource usage/unit, T_0 is the capitalization costs, S is the indirect costs, and D is the development costs.

There is no model that is assumed to be a "one-fits-all" solution. As stated above, it is left up to the individual firm to decide which model works best for its project. The information content of a product is one way to measure product complexity [37]. Because more complex products are, in most cases, more expensive to develop, information content is used as a key measurement for product development costs in the examples below.

2.3.2 Market Revenue Prediction

Predicting a product's sales can often be a very involved process. Some companies commit massive amounts of resources into predicting how a product will perform in the market and some go by gut instinct. There are methods and models that are available to alleviate some of the uncertainty and help a developer estimate the future sales of a product. The purpose of this thesis is not to prescribe a specific method to predicting how a product performs in the market, but to show how, with a given model, a developer can predict Q. This is done under the assumption that a competitor will eventually release an imitation of the product of interest to market (no sooner than the reverse engineering and imitating time). Thus, stealing market share and reducing Q for the innovator.

One model that has proven to be a good predictor of sales for a given product is the Bass Diffusion Model [26]. This model works well for the application in this thesis because it calculates how sales vary over time and not just a lump sum of sales. It has proven to be a good predictor of how quickly sales of new consumer durables grow and how much of the potential market a product can capture. The term "consumer durables" refers to products that are replaced by the consumer at a very low rate. Examples of consumer durables are refrigerators, televisions, washing machines, and lawn mowers. More recently, the Bass model has proven its adaptability by predicting the growth rate of social networking websites [38]. For this thesis, it is assumed that the product in question will have no repeat buyers; lending itself easily to the Bass Model.

The Bass model is expressed as a probability density function that spreads the total expected market sales of a product over time and is defined as

$$n(\tau) = \frac{(\alpha+\beta)^2}{\alpha} \frac{e^{-(\alpha+\beta)\tau}}{\left(\frac{\beta}{\alpha} e^{-(\alpha+\beta)\tau} + 1\right)^2} \tag{2.7}$$

where α is the coefficient of early adoption and represents the probability of an initial purchase at $\tau = 0$, and β is the coefficient of late adoption and represents the influence that previous buyers have on future buyers. Figure 2.2 is a generic representation of the Bass Diffusion curve, where the area under the curve represents to cumulative sales probability of a product.

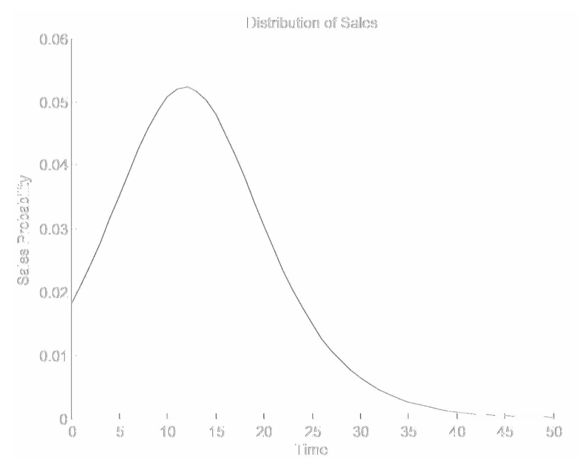

Figure 2.2: Generic representation of the Bass Diffusion Model. Note that the sales shown are not cumulative, but are time dependant.

The Bass model places buyers into two categories: early adopters and late adopters. The timing of *early adopters'* purchases is not based on how many previous buyers there have been, while the timing of the *late adopters'* purchase is based on the quantity of previous buyers. The last component needed in order to predict the quantity of sales at time, τ, is the overall market size for the entire life of the product, *m*. With the total market size estimated, the sales, Ψ, at time τ are

$$\Psi(\tau) = m \frac{(\alpha+\beta)^2}{\alpha} \frac{e^{-(\alpha+\beta)\tau}}{\left(\frac{\beta}{\alpha} e^{-(\alpha+\beta)\tau} + 1\right)^2} \tag{2.8}$$

and the time at which sales peak, or the market saturation point, is found by solving for τ when $d\Psi/d\tau = 0$. Therefore,

$$\tau_u = \frac{1}{\alpha+\beta}\ln\left(\frac{\beta}{\alpha}\right) \tag{2.9}$$

The cumulative sales Ψ_t at τ is

$$\Psi_t(\tau) = m\int_0^{\tau} n(\tau)d\tau \tag{2.10}$$

Calculating the available market size at the time of a competitor's market entry is not readily provided by the Bass model, but can be obtained by integrating Equation 2.11, subtracting the result from one and multiplying by m. Unfortunately, this only provides a portion of the competitor's market potential, because it does not account for T_M^* relative to τ_u. As stated by Krishnan [28], the ability of a competitor to capture market share is a function of how close T_M^* is to τ_u. Therefore, a competitor's market share is expressed as

$$m_c = m\left(1-\frac{T_M^*}{\tau_u}\right)\left(1-\frac{e^{-(\alpha+\beta)T_M^*}}{\left(\frac{\beta}{\alpha}e^{-(\alpha+\beta)T_M^*}+1\right)^2}\right) \tag{2.11}$$

It should be apparent that in using the Bass Model, obtaining a good prediction of sales is based upon good estimates of α, β, and m. Obtaining good estimates of α, β, and m can be done in various ways, but one simple way is to use data from a similar product and market. Research suggests that when time is in years an average value for α is 0.03, but is often less than 0.01, and β ranges between 0.3 and 0.5 with an average value of 0.38 [39]. The parameters should be scaled according to the time scale. It is important to emphasize that this discussion of the Bass model has been to facilitate the discussion of how a given sales model can be applied to make design decisions based on the resulting estimate of Q. Once again, it is not being suggested that the Bass model is one that should be used for all applications. Firms should use discretion when deciding what model to use to estimate the sales of its product.

2.4 Return on Investment Calculation

Calculating Q starts with estimating the costs and revenues of the product. The costs are broken down into two categories: development and manufacturing. The product development time is calculated using a baseline cost and the reverse engineering metrics with an information flow rate specified for development. This flow rate is simply the estimated rate at which a piece of product information is developed. In most cases, firms will be able to relate product development time to cost, because they will know their costs per time to utilize their resources. Therefore, product development cost has a linear relationship with product information content and is defined as

$$C_d = C_\tau \tau_d \tag{2.12}$$

where C_τ is the cost per unit time and τ_d is the product development time.

The manufacturing cost correlates directly with sales and is defined as

$$C_g = C_m \Psi(\tau) \tag{2.13}$$

where C_g is the cost of goods sold, C_m is the unit cost of manufacturing. The total product cost is defined as

$$C = \int_0^{\tau_d} C_d d\tau + \int_{\tau_d}^{\tau_f} C_g d\tau \tag{2.14}$$

where τ_f is the time at which the product reaches the end of its life.

The revenues for the product are obtained using the Bass Diffusion model, but with one caveat: the sales will be diminished by the entrance of an imitation to the market, thus affecting the distribution and quantity of sales. To accomplish this, $\psi(\tau)$ is first calculated assuming that no imitation enters the market. Second, the amount of market that an imitation is able to capture is calculated. Predicting the rate and magnitude at which an imitation will sell is done using the Bass model as well. An *early adoption* and *late adoption* rate, α_c and β_c respectively, is defined for the imitation product and the potential market size is reduced to what is currently remaining after sales of the innovative product. Actual sales for the innovator are then defined as

$$X_t(\tau) = X(\tau) - X_c(\tau) \tag{2.15}$$

where $X_t(\tau)$ is the total sales in dollars for the innovator up to time τ, $X_(\tau)$ is the cumulative potential market sales in dollars at τ, and $X_c(\tau)$ is the cumulative sales in dollars for the competitor at τ.

An alternate approach to calculating Q is to choose a required Q for a project. Then, designers can solve for the information flow rate needed to achieve the required Q. Once the information flow rate is calculated, designers can use intuition and/or estimation methods outlined by Harston and Mattson to decide if the flow rate will, in reality, allow the firm to capture the required Q.

CHAPTER 3. CASE STUDIES

3.1 Case Study: KitchenAid Stand Mixer

In order to illustrate how the models described above are used together, a KitchenAid Stand Mixer will be examined. According to Euromonitor International [40], KitchenAid sold approximately 24 million units of kitchen appliances from 2005 to 20010. KitchenAid has numerous product offerings, but this example will focus on its popular stand mixer. Based on the number of different kitchen appliances offered, the data provided by Euromonitor, and the Stand Mixer being KitchenAid's number one selling product, it is estimated that the market size for the stand mixer is 10 million units. To illustrate the return on investment analysis for implementing barriers to reverse engineering, the Bass diffusion model will first be invoked where no barriers have been strategically implemented, and a competitor is introduced. Under this scenario, KitchenAid's return on investment is calculated to be 1.145. This means that the project will return 100% of the costs for the product plus 14.5% above the total cost. Second, strategic barriers to reverse engineering and imitation are introduced, and the Bass model is re-executed. Though there is added cost of designing and manufacturing the barriers, material barriers can be used to achieve a 6.4% gain in Q.

The parameters used in this example are listed in Table 3.1. The development rate, F_d, is set to 0.036, which is the rate at which barriers can be designed into the product in units of information per hour. The parameters $F_R(1)$, $F_I(1)$, $K_R(1)$, and $K_I(1)$ are the geometry flow rate and information content of the stand mixer as they pertain to reverse engineering and imitating. The parameters $F_R(2)$, $F_I(2)$, $K_R(2)$, and $K_I(2)$ are the material microstructure flow rate and information content of the stand mixer. Notice that $F_R(1)$ and $F_I(1)$ are noticeably larger than $F_R(2)$ and $F_I(2)$. This is simply due to the fact that geometric information (i.e., dimensions) can be extracted much faster than microstructure information (i.e., effective size, effective orientation, and distribution of crystallographic grains). The values chosen for $F_R(2)$, and $F_I(2)$ are based upon

h

Figure 3.1: KitchenAid Artisan Stand Mixer. [1]

the research conducted by Takahashi et al. [41]. They found the average time for material sample preparation and material scanning with orientation imaging microscopy was around 36 hours, but can far exceed that in many instances. The power exerted by KitchenAid's product development team to develop the stand mixer is represented by P_d. The reverse engineering and imitating power is represented by P_R and P_I, respectively. Recall that these values are set to "1" as it is the most conservative approach.

For the first case presented, there is no intentional barrier implemented. It is assumed that the mixer is composed of a single material and that the material type could be fully defined by to pieces of information: a simple hardness test and a chemical test. Therefore, $K_R(2)$ is assigned a value of 2. The value for $K_I(2)$ is assigned based on the quantity of manufacturing information required to replicate or obtain the material. In this instance, it is assumed that 4 pieces of manufacturing information are required. Specifically, the type manufacturing process (i.e. casted or milled), the required heat treating, the required cold working, and how to acquire the raw material.

As stated above, the Bass model is invoked to illustrate the diffusion of the stand mixer market. The parameters α and β are the coefficients of early adoption and late adoption, respectively, for the Bass model. The values for these coefficients were chosen based on research presented by Sultan et. al. [42] for both KitchenAid's stand mixer and the competitor's product. The retail price is represented by ρ. The cost for KitchenAid to manufacture the stand mixer is represented by C_m. Note that the product development costs, C_d, include all pre-launch costs, including engineering costs, marketing, tooling, and production ramp-up (30 day supply of product) and are evenly distributed over the development time.

For this example, the assumption is made that the stand mixer is a new and innovative product and that the percentage of market share a competitor can capture is inversely proportional to its launch time as shown in Equation 2.11.

Figures 3.2, 3.3, 3.4, and 3.5 (plotted on the same scale for ease of visualization) aid in visualizing how the costs and revenues are distributed over the life of the product. Figure 3.2 illustrates the distribution of development costs. Figure 3.3 illustrates the distribution of sales starting immediately after product launch and if an imitation product is never released. Figure 3.4 illustrates the sales of an imitation released at $T_M^* = 4,771$ hours. Figure 3.5 illustrates the cost of goods sold over the life of the product and accounts for the release of an imitation. These figures can then be superimposed to make a composite graph, as represented in Figure 3.6. Note that in Figure 3.6 there is very short period where KitchenAid is alone in the market, which is depicted by the "spike" in sales immediately after development. This is also the reason for the apparently vertical line in Figure 3.5.

The return on investment is calculated through integration as

$$Q = \frac{\int_{\tau_d}^{\tau_f} \Psi(\tau) - \Psi_c(\tau) d\tau}{C_d \tau_d + \int_{\tau_d}^{\tau_f} C_m d\tau} \tag{3.1}$$

Q can also be visualized as the ratio of the difference in areas under the curves of Figures 3.3 and 3.4 to the sum of the areas under the curves of Figures 3.5 and 3.2. From the model, Q is calculated to be 1.145. Also, the calculated barrier is $1.3 \times 10^{-}3$.

Table 3.1: Input parameters for calculating return on investment of a KitchenAid mixer.

Param.	Value	Decription
F_d	0.036	Development rate (units of information per hour)
$F_R(1)$	144	Reverse engineering geometry information flow rate (units of information per hour)
$F_R(2)$	0.4	Reverse engineering microstructure information flow rate (units of information per hour)
$F_I(1)$	50	Imitating geometry information flow rate (units of information per hour)
$F_I(2)$	0.1	Imitating microstructure information flow rate (units of information per hour)
$K_R(1)$	800	Reverse engineering geometry information (units of information)
$K_R(2)$	2	Reverse engineering material information(units of information)
$K_I(1)$	300	Imitating geometry information (units of information)
$K_I(2)$	4	Imitating material information (units of information)
P_d	1	Development power
P_R	1	Reverse engineering power
P_I	1	Imitating power
α	2.03×10^{-5}	Coefficient of early adoption for analysis in hours
β	5.64×10^{-4}	Coefficient of late adoption for analysis in hours
α_c	3.00×10^{-5}	Competitor's coefficient of early adoption for analysis in hours
β_c	6.00×10^{-4}	Competitor's coefficient of late adoption for analysis in hours
m	10.00×10^6	Market size in number of units
ρ	250	Product retail price in Dollars
C_m	200	Cost to manufacture product in Dollars
C_d	$14,500$	Development cost in Dollars per hour

KitchenAid can influence Q and B by incorporating different types of information and/or by varying the quantity. Doing so will likely affect the product development time, cost, and manufacturing cost, however, the added barrier will also likely delay the competitor's market entry. It is important to understand this tradeoff in order to effectively increase Q by implementing barriers. For the above example, assume KitchenAid strategically manipulates the material microstructure of the stand mixer in order in increase the barrier. Because the analysis of a given material's microstructure is intricate and time consuming, there will be a significant change in F for the competitor. Due to the increased difficulty of extracting microstructure information and added information the values of the following parameters are changed: $F_R(2) = 0.04$, $F_I(2) = 0.01$, $K_R(2) = 15$, and

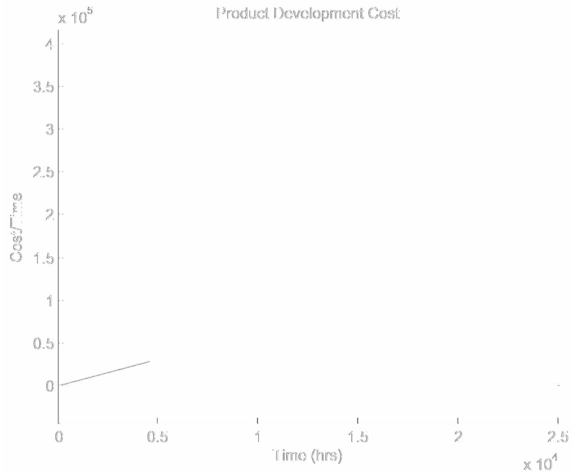

Figure 3.2: Estimated per time product development costs.

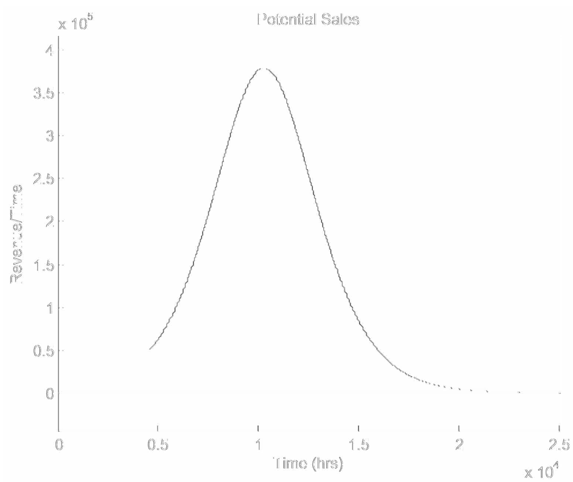

Figure 3.3: Estimated per time potential sales.

$K_I(2) = 30$. The additional information included in the product also increases the product development time, cost, and the manufacturing cost. The addition of more information and a slower information flow rate for the competitor results in $T_M^* = 14,797$ hrs. This change leads to $Q = 2.48$, which provides the firm with an extra 3% return over what was previously calculated. This equates to an extra \$311 million in net sales for KitchenAid. Also, the barrier is improved to 78.0×10^-3. It is important to note that the barrier values are intended as a comparative measure. Typically the barriers of various designs are compared to the barrier of a benchmark design. The product

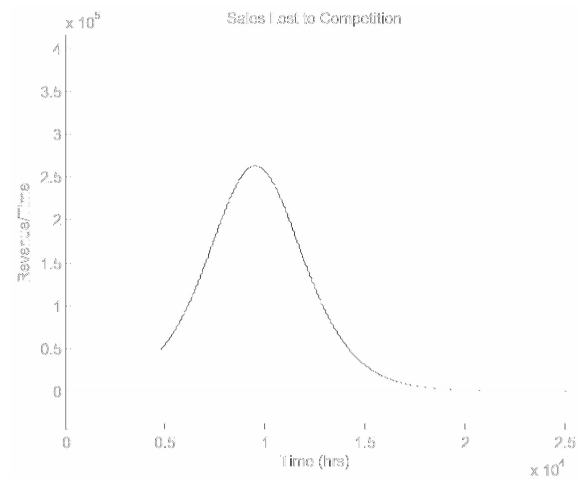

Figure 3.4: Estimated competitor's sales as a result of releasing an imitation. In other words, sales lost to the competitor.

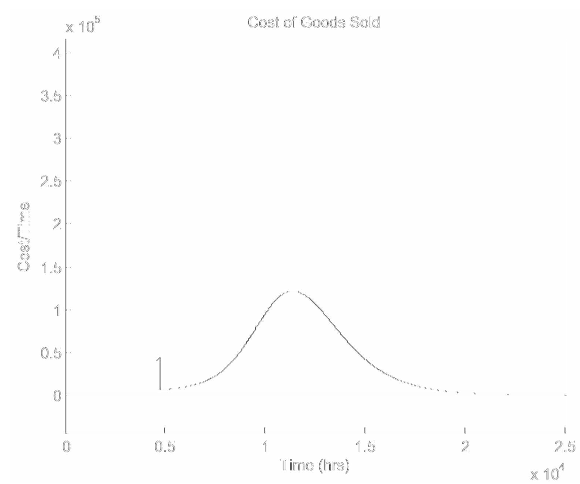

Figure 3.5: The estimated cost of goods sold over the life of KitchenAid's stand mixer.

life-cycle plot for the improved barrier is shown in Fig. 3.7. A substantial change in the revenues of KitchenAid's stand mixer can be noticed from the plot alone.

3.2 Case Study: Cantilevered L-Beam

The above has illustrated how incorporating different types of information can increase the barrier and time to market entry for a competitor, thus increasing the return on investment for the innovator. The following case study will illustrate the implementation of specific barriers and how

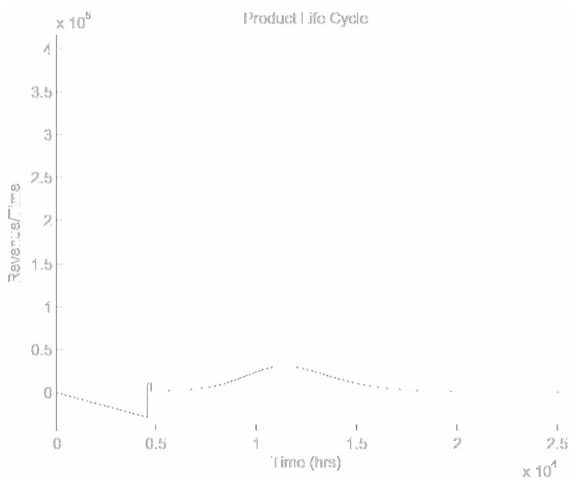

Figure 3.6: The estimated per time costs/revenues of KitchenAid's stand mixer over its entire life.

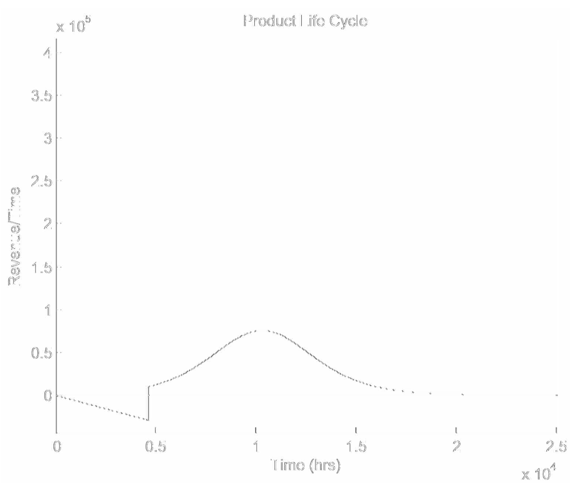

Figure 3.7: The estimated per time costs/revenues of KitchenAid's stand mixer over its entire life with a microstructure barrier.

those affect the return on investment for the innovator. It is borrowed from Harston et al. [43] and is extended to illustrate the point at hand. Here, an "L" shaped beam is considered, as shown in Figure 3.8, which is fixed at one end and exposed to a prescribed deflection at the other. Note that this beam is unique in that the cross-section is composed of anisotropic layers, which have been joined using ultrasonic consolidation [43]. This particular beam is used as a contact in an electrical connector, hence the reason the dimensions are in millimeters.

Because of the geometric constraints of the application, the geometry for the L-beam is fixed. Harston et. al. first optimized the L-beam under four separate conditions to achieve a target

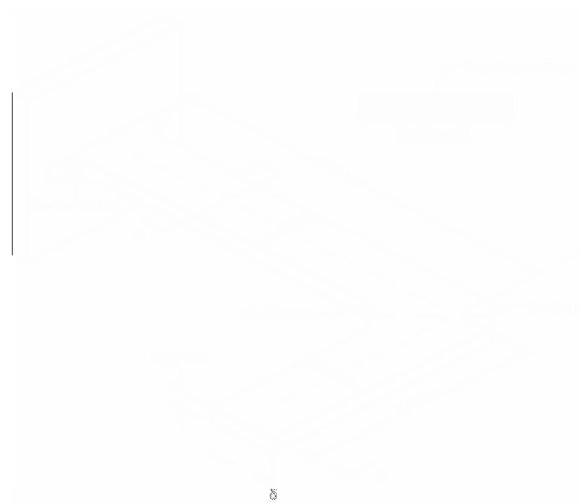

Figure 3.8: Geometry and boundary conditions for the L-beam case study.

reaction force at the free end when subjected to a prescribed displacement (δ) at the same end. The four different conditions analyzed were (I) Single Isotropic Layer, (II) Single Anisotropic Layer, (III) Multilayer Anisotropic, and (IV) Single Layer Heterogeneously Anisotropic. Condition (I) is used as a benchmark and is manufactured using traditional manufacturing techniques. Whereas, conditions (II), (III), and (IV) are manufactured using ultrasonic consolidation and/or friction stir welding [43]. Table 3.2 specifies the constant input parameters that will be used to calculate Q for each condition. The amount of information contained by each condition will vary, as specified in Tables 3.3 and 3.4.

It must be emphasized that Harston et. al. only optimized product features to match a specified measure of performance – the reaction force – and did not attempt to optimize Q. In this case study, the L-beam is further analyzed to obtain Q for each of the four conditions. Because each condition will require slightly different processes to manufacture, the manufacturing costs are adjusted to reflect that. Furthermore, when a product is truly innovative the sales price will not be dictated by competitive products. Therefore, we are able to adjust the sales price to overcome the added expense of barrier implementation. Due to the added barriers, the market becomes more secure and there is less threat of having to compete on price. However, it is important to also consider the impact that a higher sales price will have on the overall market size. On the other hand, frequently there are constraints on the sales price of a product. For this purpose, we present

Table 3.2: Constant input parameters for calculating the return on investment of a cantilevered L-beam.

Param.	Value	Decription
F_d	0.036	Development rate (units of information per hour)
$F_R(1)$	144	Reverse engineering geometry information flow rate (units of information per hour)
$F_R(2)$	0.04	Reverse engineering microstructure information flow rate (units of information per hour)
$F_I(1)$	50	Imitating geometry information flow rate (units of information per hour)
$F_I(2)$	0.01	Imitating microstructure information flow rate (units of information per hour)
P_d	1	Development power
P_R	1	Reverse engineering power
P_I	1	Imitating power
α	3.00×10^{-5}	Coefficient of early adoption for analysis in hours
β	3.00×10^{-4}	Coefficient of late adoption for analysis in hours
α_c	6.00×10^{-5}	Competitor's coefficient of early adoption for analysis in hours
β_c	4.00×10^{-4}	Competitor's coefficient of late adoption for analysis in hours
m	1.00×10^{8}	Market size in number of units
C_d	$1,000$	Development cost in Dollars per hour

Q under two scenarios – a fixed sales price, and a variable sales price. The results of the analysis are presented in Tables 3.3 and 3.4, respectively.

Table 3.3: Input parameters for return on investment of a cantilevered L-beam with varying mechanical properties, which has been optimized to achieve a target reaction force for a prescribed deflection. Retail price is held constant.

Case	$K_R(1)$	$K_R(2)$	$K_I(1)$	$K_I(2)$	C_m (\$)	ρ (\$)	T_M^* (hrs)	Q
(I) Benchmark	10	2	30	4	0.02	0.10	$2,140$	3.826
(II) Single layer	10	3	30	6	0.04	0.10	$2,858$	2.253
(III) Four Layers	14	15	42	30	0.06	0.10	$11,726$	1.558
(IV) Heterogeneous	10	18	30	36	0.05	0.10	$13,642$	1.855

Let us first discuss Q when there is a fixed sales price as seen in Table 3.3. Notice that for this example, when the sales price is fixed, Q decreases as barriers are implemented. This

Table 3.4: Input parameters for return on investment of a cantilevered L-beam with varying mechanical properties, which has been optimized to achieve a target reaction force for a prescribed deflection. Retail price varies.

Case	$K_R(1)$	$K_R(2)$	$K_I(1)$	$K_I(2)$	C_m (\$)	ρ (\$)	T_M^* (hrs)	Q
(I) Benchmark	10	2	30	4	0.02	0.05	$2,140$	1.531
(II) Single layer	10	3	30	6	0.04	0.08	$2,858$	1.803
(III) Four Layers	14	15	42	30	0.06	0.12	$11,726$	1.869
(IV) Heterogeneous	10	18	30	36	0.05	0.10	$13,642$	1.855

is due to the increased product development and manufacturing cost that is unable to be recovered even though the product is able to capture and maintain a larger portion of the market share. This demonstrates that not all products will benefit from implementing barriers. As an alternate approach, one can consider additional barrier types and model their impact on Q.

However, if the product is innovative and the market is secure, the sales price can be adjusted to help recover the increased product development and manufacturing costs. Notice that Q differs for each condition in Tab. 3.4, but the difference in Q between conditions (III) and (IV) is minimal. This relatively small change is due to the fact that the competitor release time is far beyond the market saturation point. Condition (IV) has slightly lower development and manufacturing costs, thus the slightly higher Q. For the four conditions considered here, condition (IV) yields the highest Q. However, in order to minimize the impact on development costs, in most cases, the competitor launch time should be shortly after the market saturation point. In some instances, the cost to increase T_M^* beyond the saturation time may be relatively insignificant and careful consideration must be given to costs. Therefore, the optimal condition may be a design that fits between (II) and (IV). This optimal condition, in theory, would yield the maximum Q for this product. This example illustrates that more information may further delay a competitor's release, but can also result in a lower Q. Thus, in order to maximize Q, it is important to consider all tradeoffs, including both information type and quantity, when implementing barriers into a design.

CHAPTER 4. CONCLUSION

The implementation of barriers to reverse engineering and imitating has its most pragmatic impact when it results in a larger Q than any other alternative. The launch of the imitation can have a significant impact on Q of an innovator's product, because it steals away market share and reduces sales from what they could potentially be. In order to understand how implementing a barrier strategy affects Q, a framework has been developed that considers T_M^*, the market diffusion of a product, and the influence a competitor has on that market diffusion. In order to facilitate the development of that framework, proven theories in time to reverse engineer and product, information extraction flow rate estimation, and product market diffusion have been used and integrated through the three new developments. These include: (i) the barriers to imitation metrics, (ii) the manipulation of the Bass Diffusion model to account for a competitor's market entry, and (iii) the final return on investment metric that includes elements of barriers to reverse engineering, barriers to imitation, and the market diffusion model. Although this is not able to be fully tested within the scope of this research, the metrics have been narrowed down to costs and time. Through a sensitivity analysis, it was found that Q is most sensitive to changes in m. Therefore, decision makers must obtain the best possible estimate of m.

In calculating Q, tradeoffs need to be managed. The two main tradeoffs to consider are product development costs and time to competitor market entry, specifically the implementation of barriers. Firms can spend a large amount of money to indefinitely delay a competitor from reverse engineering, imitating, and releasing an imitation product, but this will most likely not result in the largest return on investment. If product development costs are carefully balanced with the implementation of barriers to reverse engineering and barriers to imitating, firms can maximize Q for a given project.

The discussion of existing market models has been brief and it is recommended that a firm seeks out models that best fit its situation. Also, is has been suggested that F can be obtained by methods presented by Harston and Mattson or setting a required Q and solving for F. Either method is acceptable. The key to successful application of the reverse engineering and imitating metrics is a good estimate of F.

This thesis has also discussed microstructure manipulation as an approach to creating barriers to reverse engineering and imitating. An enabling technology is ultrasonic consolidation, which can be used to bond thin anisotropic metal foils together. The other approach which has been suggested is using various material processing techniques to generate a strain path that is difficult to duplicate. The overall implication here is that the most effective barriers are often at a microscopic level. However, the implementation of these barriers often come at a cost and the return on investment analysis developed in this thesis provides designers with a practical way to measure the tradeoffs associated with those costs.

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