Enabling Effective Product Launch Decisions

by

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Abstract

The present work looks into the question of optimizing the performance of product launch decisions—in particular, the decisions of product development duration and manufacturing ramp-up. It presents an innovative model for measuring product launch performance and optimizing the decisions by integrating a design structure matrix model for product development, a technical cost model for manufacturing, and revenue and warranty models for customer reaction to product quality into one model using net revenue as a metric. The model shows that overlooking the interactions between product development and manufacturing leads to suboptimal decisions. Furthermore, it points out that product quality is apparently the most important driver for product launch performance and that the effects of product launch decisions on resulting product quality need to be considered. Results from case studies demonstrate that improving firm's tactical strategies will help shorten product launch and improve its performance, while factors such as low reputation or high product failure rate will require lengthening product launch to minimize their impacts. Finally, the model results are analyzed to yield direction for firms relative to strategies that can be implemented to improve product launch performance. The most effective strategy is one that improves the PD capability (higher ability to find and fix problems) and the second most effective is to improve problem solving in manufacturing ramp-up.

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1 Introduction

The manufacturing industry is facing multiple challenges: continually changing technology, fierce competition on a global scale, nearly identical products due to similar technologies and common components, and well informed customers. (Murthy and Djamaludin 2002) In the past, firms could rely primarily on steady state operations to turn a profit; transient events in operations occurred, but were generally noncritical to the firm's performance. Increasingly, this is changing.

Product innovations and market competition are driving firms to shorten product lifecycles and introduce new products at a seemingly ever faster pace. Firms need to release new products faster simply to 'keep up with the game.' There is evidence of increasing number of products release per firm in the past 20 years, as presented in Figure 1-1. (Bayus 1998) This trend has significantly increased the importance of 'regular' transient behavior operations such as product launches.

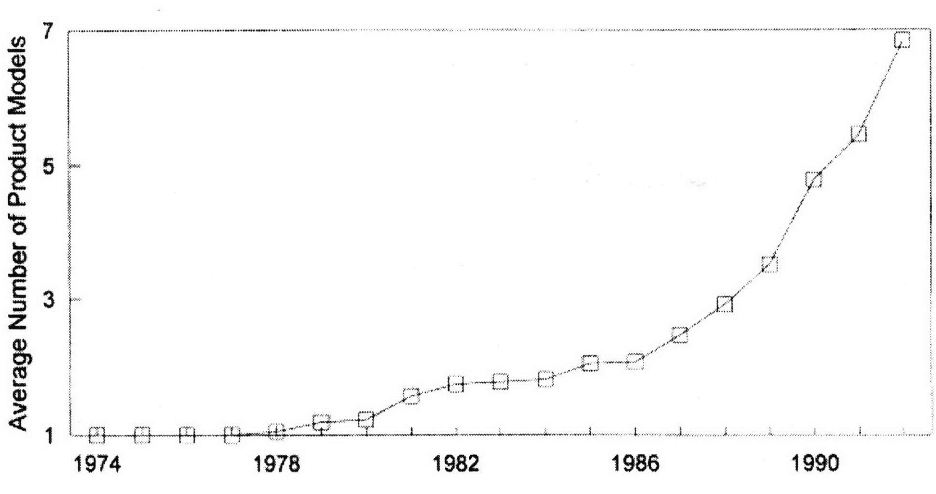

Figure 1-1: Average Number of Product Models per Firm in Personal Computer Industry (Bayus 1998)

Manufacturing product launch is the process of introducing a new product or new features in an existing product into a firm's production operations. It can have a substantial impact to the firm's operation depending on the complexity of the new product or new features. In the automotive industry, for example, Ceglarek et al. (2004) claims that product launch used to occupy approximately 5% of a product's lifecycle 10 years ago, while now it can represent as much as

20% of that lifecycle, where product lifecycle is defined as the time between the first manufactured product until the time it is withdrawn from the manufacturing facility. (Polli and Cook 1969) From the manufacturing perspective, product launch can cause a disruption due to process change or process addition, resulting in the production line slowing down and/or decreasing product quality. During manufacturing launch, the facility either slows down the manufacturing rate of the new product to avoid encountering too many problems in the beginning or keeps the rate constant but suffers yield loss. This transient period operation can range from a few weeks to months. Depending on the problem solving process during manufacturing, the facility will increase the manufacturing rate until eventually it is at full capacity. This process is called *manufacturing ramp-up.* The manager must make decisions on the manufacturing rat of each period.

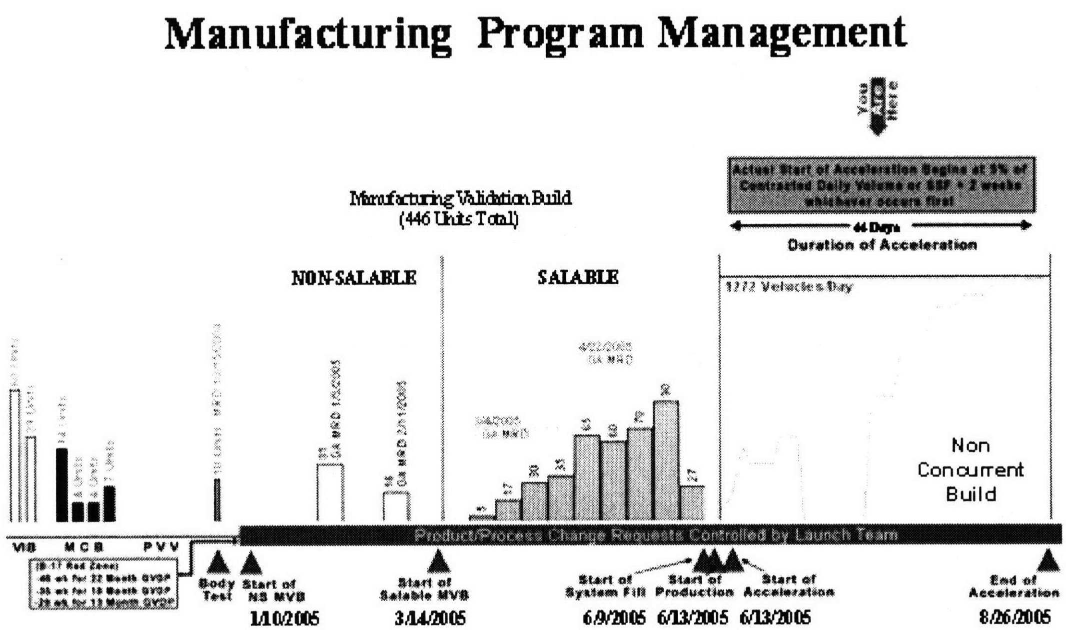

Figure 1-2: Typical Automotive Manufacturing Launch

However, introducing a product is more than just manufacturing. There are multiple processes that come before manufacturing launch, referred to collectively as product development (PD). PD consists of conceptual design, detailed design, prototyping, and testing and validation. During product development, the development team works on product concepts and design parameters and at the same time eliminates potential problems arising from the design. Ideally, the team will attempt to eliminate all design problems before submitting the design to be manufactured. However, due to time pressure and realistic resource limitations, the team is never able to eliminate all the problems and some make it through to manufacturing. These defects affect the amount of manufacturing errors encountered and the quality of the finished products. The manufacturing errors increase the manufacturing cost, while the finished product quality will influence the firm reputation and demand for the products.

Manufacturing costs can be divided into fixed costs and variable costs. The fixed costs are generally associated with capital investments, while the variable costs are dependent on the production volume. By definition, variable costs are constant on a per unit product basis. Therefore, when considered as total variable cost, they are generally thought of as directly proportional to production volume. In matured processes, where changing cycle time has virtually no impact on the rate of errors, variable costs would remain relatively constant regardless of cycle time choice. However, in the case of manufacturing launch, where manufacturing processes are new and prone to errors, changes in production volume may lead to considerable changes in the rate of errors, forcing the manager to make different cycle time decisions, which influence the total variable costs.

The finished product quality can also suffer during product launch. Unresolved design problems that exist during manufacturing and are not eliminated stay in the final products, resulting in low product quality. Low product quality affects the customer perception of firm reputation, leading to low demand and revenue.

With the complexity and implications of product launch, manufacturing facility managers have multiple operating parameter decisions to make, such as the start of launch and manufacturing rate. In this case, manufacturing models are useful to help managers explore manufacturing strategies and anticipate the results. However, if the managers fail to realize the interaction between product development, manufacturing, and product quality,

Because the ultimate goal of a firm is to maximize profit, a firm needs to understand that product launch is not merely the introduction of new parts and processes in a manufacturing facility. It is, in fact, a much larger process that is inseparable from product development and affects the sales of the firm even after the launched product is withdrawn.

1.1 Background

To understand the transient behaviors taking place during product launch, background information of each process will be explored. Relevant literatures are reviewed to understand the latest progress in the research community on the topics and identify unexplored area for which this dissertation may contribute.

1.1.1 Manufacturing

Normally, even before volume manufacturing begins, there are several product development activities that require the manufacture of prototypes to test. Similarly, even while volume production is beginning, firms are still developing the product particularly with regard to modifications that eliminate operational issues. Nevertheless, to simplify the subsequent framework discussions, manufacturing will be defined as the period of a product's lifecycle that begins the first time the new product or the new feature of a product is manufactured in a volume production facility and lasts until the product is phased out of that facility.

A facility manager needs to make decisions on how to proceed concerning manufacturing ramp-up. The process is complex and involves efforts from workers and supervisors from all parts of the production line. By decreasing the rate, the facility will encounter fewer disruptions or manufacturing events, but it will produce fewer products and vice versa. While the fewer number of errors is desirable, the errors are important in manufacturing learning process. (Li and Rajagopalan 1997) The process of manufacturing learning is crucial to manufacturing ramp-up. Errors will help workers learn to deal with manufacturing events and potentially eliminate the source of problems, allowing the manager to increase the manufacturing rate without suffering overly from manufacturing events.

A large body of literature addresses the importance of enhancing the production capacity during manufacturing ramp-up. Chand et al. (1996) focus their research on the decision of allocating productive capacity between production activities and improvement activities. Li and Rajagopalan (1997) study the impact of part quality on learning rate. Several authors also point out the significance of process changes to improve firm's manufacturing capacity. Carrillo and Gaimon (2000) modeled investments on process change and knowledge creation from planning and training versus process improvement and gave recommendations on investment strategies on these items. Terwiesch and Xu (2004) study the tradeoff between capacity enhancement from process change and learning during manufacturing ramp-up.

Although with the amount of literature available on product and process improvement during ramp-up, the questions dealing with decisions during ramp-up still remain relatively unexplored, as commented in the review of literature by Krishnan and Ulrich (2001). There are, however, a few exceptions. Terwiesch et al. (2001) indicated that the high-tech firms are shifting from minimizing time-to-market to minimizing time-to-volume and studied the problems during manufacturing ramp-up in data storage industry. Terwiesch and Bohn (2001) proposed the modeling of manufacturing ramp-up as manufacturing period with experimentation that results in additional cost and lower utilization, but contributes to learning and process improvement. However, in this work, the variable cost per unit is independent of operating conditions. Terwiesch and Xu (2004) consider the tradeoffs between process/recipe changes and learning during the experimentation and the manufacturing ramp-up period. Bayus (1995) developed a dynamic model of product innovation where the tradeoffs between investments on product improvement and process improvement are considered. Carrillo and Franza (2006) developed a model to determine the best product development duration and ramp-up time based on the investment in product design and manufacturing capacity.

Most of the literatures dealing with manufacturing ramp-up decisions uses production volume as the decision. In fact, Terwiesch and Bohn (2001) suggests the actual decision a manager makes during ramp-up is cycle time, which influences the amount of defective parts and, therefore, yield; the variable cost is assumed constant regardless of cycle time. However, the choice of cycle time can influence the variable cost: cycle time choice leads to difference rate of manufacturing problems which not only affects in defective parts, but also interruptions, reworks, and maintenance. As cycle time and production ramp-up are decisions which will directly affect the variable cost, there are good reasons why these variables should be treated more rigorously.

1.1.2 Product Development

Krishnan and Ulrich (2001) define product development as the transformation of a market opportunity and a set of assumptions of product technology into a product available for sale. They also state that decisions regarding product development can be categorized into two types:

decisions in setting up a project and decisions within a project. Decisions in setting up a project have to do with product strategy and planning, product development organization, and project management. These decisions deal with higher, organizational level of product development such as the target market for the product or resource prioritization for different projects. Decisions within a project, on the other hand, deal with the operational level of product development such as design parameters for products, component suppliers, and product launch.

The decisions regarding product development that a manager will have to consider are operational level: the start of new product manufacturing or manufacturing launch. By setting a deadline for the product development team to finish product design, the manager essentially makes the decision on the product development duration, which will have significant effects on the cost and quality of the product design.

There has been extensive research in the area of tradeoffs between product performance, profit, and time to market. The focus of these studies is to evaluate the optimal product launch start and the effect of competition from other firms in the market. Bayus (1997), Cohen et al. (1996), and Wang (2005) studied the tradeoffs between product performance and product development duration and presented the optimal product launch time with respect to exogenous factors such as size of potential market, profit margin, and firm's speed of product improvement. Cohen (2000) also added that overly relying on certain standard metrics for product development such as time-to-market or product performance target can lead to less than optimal decisions. Savin and Terwiesch (2005) studied the tradeoff of lost revenue from launch delay from market competition and lowering production cost and suggest the existence of an optimal launch time in a duopoly. Clark (1989) studied the effect of part sharing strategy and its effect on product development performance, profitability, and launch time. Gerwin and Borrowman (2002) give a thorough overview of the role firm's cross-functional integration can play in reducing time-to-market of new product development.

Several authors provide qualitative guidelines on how revenues are affected by a delayed versus an accelerated launch. Urban and Hauser (1993) suggest that reducing product development lead time will increase life-cycle sales at a diminishing rate, and that it will increase overall development cost. This suggests the existence of an optimal launch time. Rosenthal (1992) showed that moving from actual introduction to the earlier, planned introduction seems to indicate sales increases at an increasing rate. The framework explicitly includes competition—assumed to begin at the time when sales start to fall—and takes the perspective of the first mover. Kalyanaram and Krishnan (1997) suggest a convex-concave relationship between product development duration and lifecycle sales, where there is a steep increase in sales with increasing duration in the middle, but further increasing (or decreasing) the duration beyond certain points will only slightly increase (or decrease) lifecycle sales. Wheelwright and Clark (1992) argue that there can be great profit associated with shortened development duration. However, overly short lead time does not yield the desired increase in profits, and can even result in profit loss. Taken together, all authors emphasize the impact of changes in product development duration on a product's life-cycle sales and profits.

However, the prior work has not addressed a way to quantify product development performance and how it affects manufacturing and finished product quality. There is also a lack the causality as to why the increase in product development duration would lead to product performance improvement or product sales increase. In order to understand how the product development duration decision affect the launch performance, this dissertation will establish the relationship between product development duration and performance and how the performance affect manufacturing launch and product quality.

1.1.3 Customer Reaction to Product Quality

After a product is manufactured, its finished quality will have impact on revenue and additional cost incurred to the manufacturing firm. When the product breaks down or needs a replacement, the service and/or the part cost is charged to the manufacturer: the higher the product quality, the less likely the chance of it breaking down or being defective. High quality products will also create reputation or 'customer goodwill,' which leads to high demand and potentially high revenue, and vice versa.

1.1.3.1 Warranty Cost

In the purchase decision of a product, buyers usually compare characteristics of products of competing brands. However, in modern manufacturing, the business is characterized by continually changing technology, global markets, nearly identical products due to similar technologies and common components, and well informed customers. (Murthy and Djamaludin

2002) It is, therefore, increasingly difficult to make decisions on the best product. In this case, post-sale factors such as warranty, parts availability and cost, and service and maintenance are becoming more important in product choice. Additionally, with rapidly changing technology, later generation products tend to be more complex than the ones they replace. Customers are often uncertain about new product performance. As such, warranty will play a significant role in giving customers insurance they need to purchase the products.

Firms will need to consider warranty as part of a post-sale service strategy, since it can incur additional cost beyond that of the product development and manufacturing. Warranty cost typically ranges from 2% to 15% of net sales. (McGuire 1980) As a result, warranty cost has a significant impact on the manufacturing business.

According the a literature review by Murthy (2002), there has been a vast body of literature on the topic of warranty cost modeling. Murthy divides the bulk of literature into two types of modeling methods: one-dimensional and two-dimensional policy—a one-dimensional policy cover one characteristic of the product such as age, while a two-dimensional policy covers two characteristics such as age and the amount of usage—although he mentions that one-dimensional policy models receive much more attention. The models are constructed to analyze product engineering quality feedback and optimal warranty policies.

In this dissertation, in order to assess the total effect the decisions in product development and manufacturing ramp-up have on profitability of the firm, warranty cost will be taken into consideration.

1.1.3.2 Reputation

Economists have become aware of how imperfect information can cause several characteristics of market imperfections. (Shapiro 1982) While much effort has been spent on understanding the effect of uncertainty about various prices at which a product is offered (Salop and Stiglitz 1977; Wilde and Schwartz 1979), it is relatively minor and unimportant in comparison to uncertainty about product characteristics. (Shapiro 1983)

Uncertainty about quality is a widespread and important feature of markets for most firms' goods. On some products, especially consumer durables, it is virtually impossible for customers to assess the quality before purchase. Customers, therefore, relies on reputation as a signal for product quality.

Market behavior and product quality interact via the notion of reputation. According to Akerlof (1970), if product quality is given exogenously, with price offered only dependent on the average product quality throughout the market and high quality items are more expensive to produce, the market will eventually be flooded with minimal quality products if customers never learn about the reputation of each firm. Since there is no profit in 'doing more than necessary,' firms whose products are of lower quality will make the most profit as it does not have bad reputation, while high quality firms will be forced out of business. In reality, there exists an incentive for a firm to make high quality products. High quality product release can improve the reputation of the firm. Products that come from the firm with high reputation are generally believed to be of high quality, and therefore can be sold at higher quantity or higher price. The firm must be able to correctly weigh the cost and benefit of making high quality product.

While there exist a considerable amount of published papers on topic of reputation, as reviewed by Weigelt and Camerer (1988), most deal with reputation in corporate strategic decisions and economic signaling game. Only a small part of them deal with the mathematical representation of reputation. Out of these, only a few discuss the relationship between product quality, reputation, and demand. This relationship is crucial in determining the benefit and cost of manufacturing high quality product.

1.2 Problem Statement

As the literature review indicated, there is extensive research work on modeling and measuring the performance of manufacturing systems and product development during product launch. However, when dealing with the concept that product development and manufacturing are interconnected, there are only a few papers dealing with this scenario.

Carrillo and Franza (2006) developed a model to determine the best product development duration and ramp-up time based on the investment in product design and manufacturing capacity. Using the Cobb-Douglas equation, the constant streams of investments in product design and production capacity are translated to design knowledge and production capacity, respectively,

$$\dot{DK} = \alpha(DI(t))^{\beta}$$
$$\dot{PC} = \eta(PI(t))^{\gamma} \qquad (1.1)$$

where $\dot{DK}$ is the rate of increased design knowledge, DI is the product design investment, $\dot{PC}$ is rate of increased production capacity, PI is production capacity investment, α, β, η, γ are Cobb-Douglas equation parameters. Product development duration determines the amount of investments in design and design knowledge, while ramp-up time determines the investment in production capacity and, therefore, production capacity. Production volume is determined by the production capacity and demand

Profit margin, π, is a function of design knowledge, while sale is assumed to be the same as the number of manufactured products.

$$\pi = \pi(DK(t),t)$$
$$S = PV(t) \qquad (1.2)$$

$$\frac{\partial \pi}{\partial DK} > 0; \frac{\partial^2 \pi}{\partial DK^2} < 0 \qquad (1.3)$$

The model proceeds to determine the optimal product development duration by optimizing the profit over planning horizon.

The important conclusion of this literature is that there is a connection between optimal product development duration and an optimal ramp-up time. The dissertation will expand upon that result by taking a closer look at the causality as to why increasing design knowledge leads to higher profit margin and explicitly model that interaction.

To explicitly model design knowledge, design structure matrix (DSM) has been used in the literature to model the product development duration by employing its concept of dividing product development into small, interdependent activities (Browning 2001). DSM can model the issue resolution process by integrating the concepts of activity iterations and dependencies during product development. (Cho and Eppinger 2001) Although there has not been an attempt to quantify the product development performance using DSM, this dissertation will extend it to achieve that purpose. The review on DSM will be done in depth in section 3.1.

The design knowledge has both the cost and revenue implications on profit of product launch—a more refined product design leads to fewer manufacturing and customer problems and cost decrease, while also leads to higher quality product, demand, and revenue. The effect of design knowledge on cash flow of product launch will be treated more rigorously in this dissertation.

The questions arising from the gaps in prior work are:

1. What are the optimal product development duration and manufacturing ramp-up during launch?
2. Does including the consideration for product development and customer reaction to product quality change these decisions? How?
3. What are the factors that can affect product development duration and manufacturing ramp-up? How?

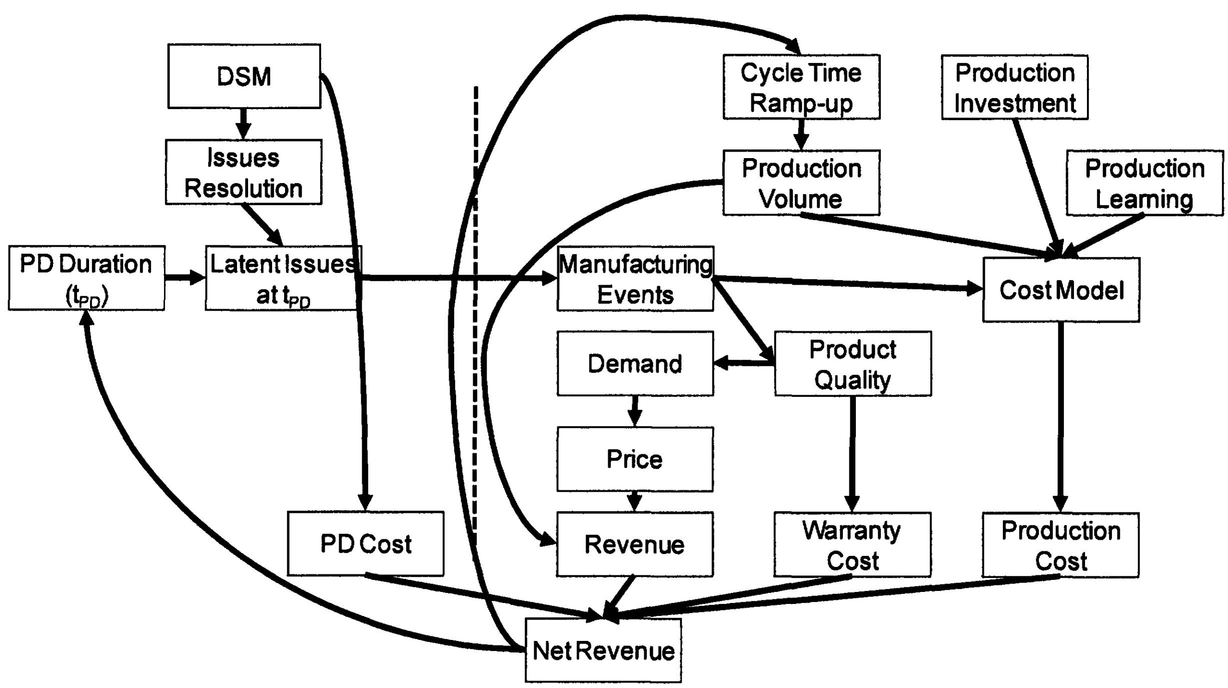

Figure 1-3: Proposed Model of Product Launch Net Revenue

To answer these questions, a new model of product launch that analyzes the interaction between product development, manufacturing and customer reaction to product quality is proposed. Net revenue is utilized as a metric to measure performance of decision variables, which are the product development duration (or manufacturing launch start), and cycle time ramp-up.

As the model in Figure 1-3 proposes, a dynamic interaction among product development, manufacturing, and customer reaction exists. The decision about product development duration is important in determining production progress when the product is introduced in a facility. Depending on cycle time (or manufacturing rate) of the facility, finished product quality is determined. The finished product quality affects the reputation of the firm and the demand for the product.

In the subsequent chapters, the mathematical formulation of the model, the dynamic interaction, and case studies will be discussed in detail. In Chapter 2, the mathematical model of product manufacturing is explored along with its extension to accommodate linkage to product development and customer reaction to product quality. In Chapter 3, the model of product development period is discussed. The dissertation will also focus on how the model is used to quantify product development performance and how that performance is used in the manufacturing model. In Chapter 4, the effect of customer reaction to product quality to firm's revenue is quantified. In Chapter 5, the model will be used to evaluate optimal product launch strategies under different product development strategies and manufacturing efficiencies and investigate the influences of exogenous factors on the decisions. Insights from the case studies will be derived and discussed. Finally, in Chapter 6, concluding remarks and opportunities for research that will add to the scope and validity of the model will be discussed.

2 Manufacturing Model

In this section, the detailed mathematical modeling of manufacturing during product launch is explored. However, to build the model and correctly measure the desired effects of product launch decisions, the metric of product launch performance must be chosen. According to the literature, the most prevalent performance metrics are throughput and profit. (Kurawarwala and Matsuo 1998; Cohen, Eliashberg et al. 2000; Haller, Peikert et al. 2003; Chen, Yeh et al. 2006) The next section discusses the advantages and disadvantages of both metrics and the better one will be chosen to represent product launch performance.

2.1 Throughput versus Net Revenue as a Product Launch Metric

In the past, manufacturing experts have used the unit of production throughput as a measure of product launch performance—especially during manufacturing. During launch, lack of experience with new processes presents a choice for manufacturers. They either operate the line at less than its maximum speed and accept the resulting negative impact on throughput, or they can force the line to operate near its maximum speed despite the inadequate training or experience and accept the increase in manufacturing problems which also produces an undesirable impact on throughput. Figure 2-1 indicates this tradeoff. Therefore, by taking those two effects into account, there exists an optimal cycle time which maximizes throughput.

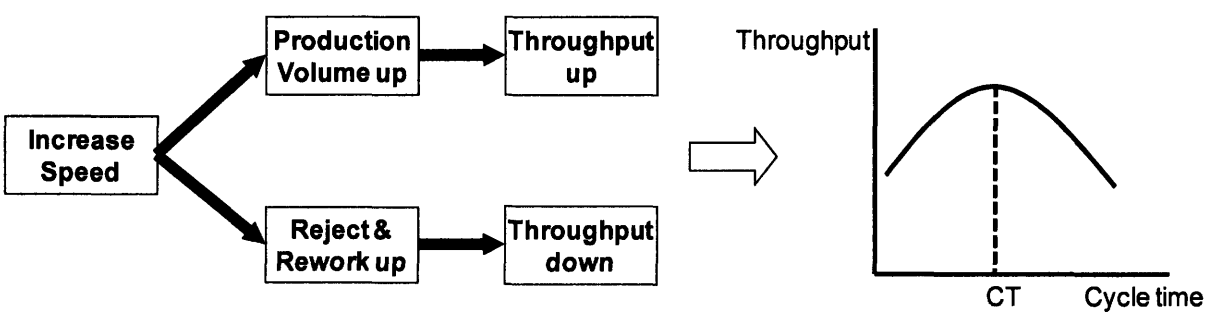

Figure 2-1: Diagram illustrating an Optimal Cycle Time under Throughput Metric

However, the ultimate goal of a firm is to maximize profit, and throughput is used as a 'proxy' for the firm's profit. While the throughput metric takes into account the loss of production due to new manufacturing processes, it entirely neglects the additional costs incurred by yield loss, additional rework, and more maintenance. This suggests that a more financial metric might be more suitable for measuring the performance of launch decisions.

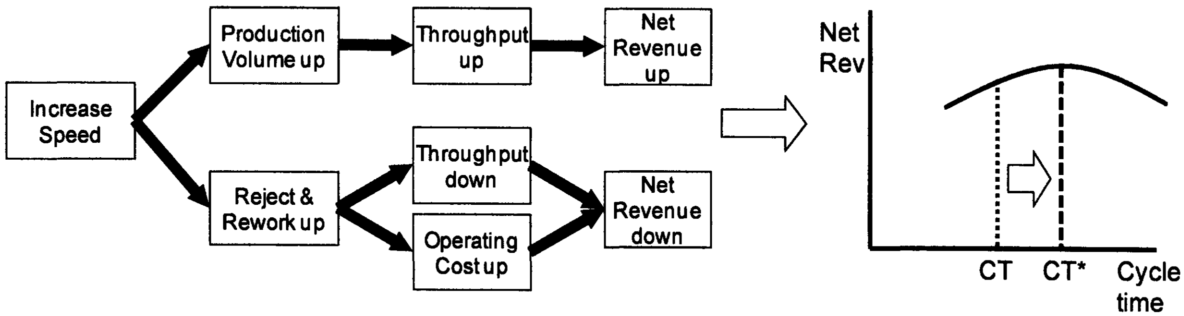

Figure 2-2: Diagram illustrating a Shift in Optimal Cycle time under Net Revenue

By considering Figure 2-2, net revenue is a closer proxy to profit than throughput since it takes into account the upside and downside of shortening the cycle time. Under net revenue maximization, there is additional tension to lengthen the cycle time which may lead to a different set of product launch decisions than under throughput maximization.

2.2 Net Revenue Model of Manufacturing

The net present value of net revenue of the launch period is defined as

$$NPV(NetRev) = \sum_{i=1}^{n} \frac{NetRev_i}{(1+dr)^i}, \tag{2.1}$$

where dr is the discount rate per period length, i is the small steady state period within the launch period. The net revenue of each steady state period is simply the revenue minus the cost.

$$NetRev_i = Rev_i - Cost_i \tag{2.2}$$

To calculate the revenue and cost for each period, the assumptions about operating conditions of product launch must be introduced and then the optimization of net present value of net revenue can be obtained.

2.2.1 Model Assumptions

2.2.1.1 Concurrent Launch

The model assumes that at the beginning of manufacturing launch, there are two types of products, A and B, manufactured at the same time, sharing the line. As the volume of B ramps up, the volume of A is phased out. The model also assumes that production of A is already in steady state, while that of B is in transitional period. The production cycle time of A is assumed fixed, while the cycle time of B can change over time. However, the cycle time of B can only be a multiple of that of A since they are sharing the same line; to vary the cycle time of B, it is customary to leave empty slots behind each B to increase the effective cycle time and allow more work time instead of slowing down the production line. Therefore, the cycle time of B is simply the number of slots it occupies times the base cycle time of A,

$$CT_{Bi} = Slot_i * CT_A. \tag{2.3}$$

2.2.1.2 Manufacturing Event

Each product is assumed to have a number of defects at the beginning of manufacturing. Each defect has the probability of causing a manufacturing event, assumed identical for all defects, which is modeled as a function of cycle time; given enough time, a worker may be able to fix an error before he has to shut down the line or before the product becomes defective.

$$\Pr_j(1\ defect) = \frac{(A_j - B_j)}{1 + \exp\frac{CT - CT_{mi}}{\Delta CT_j}} + B_j \tag{2.4}$$

where j denotes the type of manufacturing event which would result in downtime, rework, or rejected part. Note that a typical s-curve defined as in Equation (2.4) looks like:

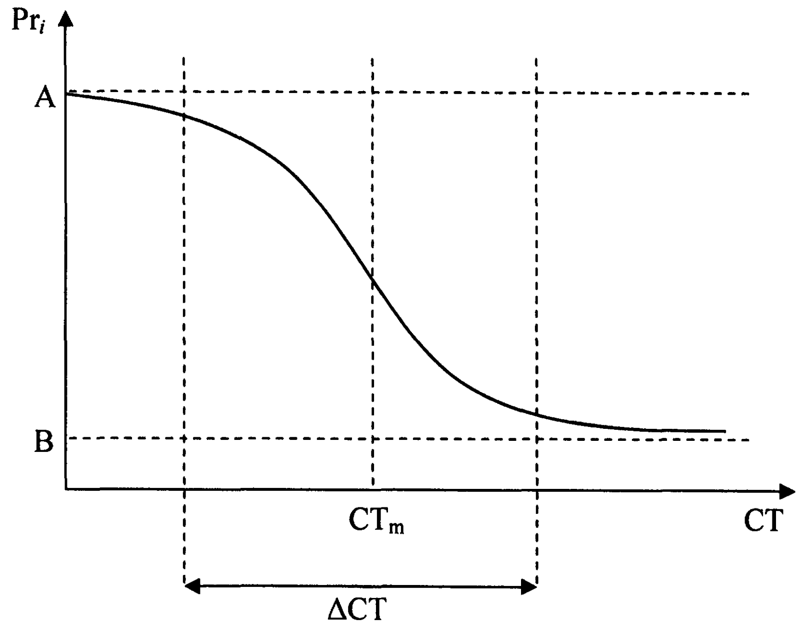

Figure 2-3: S-curve representing manufacturing event probability as a function of cycle time

In Equation (2.4), the coefficient A sets the maximum asymptote, while B sets the minimum asymptote for the curve. CT_m designates the CT that corresponds to $(A+B)/2$, while ΔCT set the 'slope' of the curve by setting the length over which the change from the maximum to minimum asymptote occurs. The reasons s-curve function is employed for the relationship between the probability of occurrence and cycle time are:

1. Pr should approach 1 as CT approaches a small value. There is a physical limit after which a line will always fail if it runs any faster.
2. Pr should decrease as CT increases. As the line runs slower, there is more time for fine tuning and careful operation, which results in a lower chance of down event.
3. Pr should approach a steady state value smaller than 1 as $CT \rightarrow \infty$. The benefit of reducing the chance of a down event by slowing down the line will be nearly negligible after a certain point. There will always be a small random chance that the machine will fail, which is unrelated to the cycle time.

If a product has d defects in it, the probability of a manufacturing event becomes

$$\Pr(d\ defects) = 1 - \Pr(1\ defect)^d . \tag{2.5}$$

As more manufacturing events are addressed, workers gather experience about the events, which may lead them to investigate the root cause of the problems and permanently eliminate the defects from all subsequent products in the manufacturing line. This process of learning is modeled using the cumulative number of manufacturing events, i.e.

$$d_{i+1} = d_i - \sum_j \Pr_j(Solve \mid Event) * \#event_{ji} \quad (2.6)$$

However, this is not the only mode of learning. Even by manufacturing without encountering events, there is a probability of improving and eliminating root cause—be it less likely, as commented by Li and Rajagolapan (1997). Therefore, equation (2.6) becomes

$$d_{i+1} = d_i - \sum_j \Pr_j(Solve \mid Event) * \#event_{ji} - \Pr(Solve \mid Volume) * PV_i \quad (2.7)$$

where $\Pr(Solve|Event)$ and $\Pr(Solve|Volume)$ are the probabilities in which the a defect is eliminated after a manufacturing event and a finished product, respectively. These probabilities can be thought of as learning rates based on manufacturing event and based on volume, and will be referred to in that way from now on.

2.2.1.3 Manufacturing Event Consequences

When a manufacturing event occurs, the system goes into a faulted state and has to stop manufacturing until it is repaired. The part that caused the event may have to be thrown away or reworked, or may not suffer any damage at all.

1. Downtime is the duration in which the manufacturing line remains in a faulted state before being repaired. The mean time to repair for each down event during period i is

$$MTTR_i = MTTR_0 \left[\frac{(\alpha - \beta)}{1 + \exp \frac{CN_i - CN_m}{\Delta CN}} + \beta \right] \quad (2.8)$$

Downtime percentage of the operating time is,

$$DT = \frac{\sum_j^n (\Pr_j(CT)_i * MTTR_i)}{CT} \quad (2.9)$$

where $MTTR_0$ is the initial mean time to repair. Mean time to repair is assumed to be learning. Again, the reason s-curve is used to represent learning is because it can be described with maximum value, α, and minimum value, β. The learning rate can be controlled by ΔCN, while CN_m controls where the maximum learning rate occurs.

2. Rework or reject: if the down event causes the line to manufacture defective products, they can either go through to a parallel line for rework, or be discarded as scrap. It is assumed that the defective products are found immediately. The rework rate (RW) and the reject rate (RR) of each period i are determined by the probability of a down event resulting in each of those actions.

$$RW_i = \bigcup_{j=1}^{n} \Pr_{REWORKj}(CT_i) \tag{2.10}$$

$$RR_i = \bigcup_{j=1}^{n} \Pr_{REJECTj}(CT_i) \tag{2.11}$$

where j signifies the type of manufacturing event.

2.2.1.4 Available Production Time for New Products

The model assumes that the production line has two types of operation time available. One is fixed normal operating time where the target production volumes of A and B are given. The other is optional overtime, which allows for some manufacturing flexibility, but has an upper bound. The model assigns operating time first to complete the required number of product A, and then assigns the remainder of the available time to the production of vehicle B. If the target production volume of vehicle B can be produced within the normal operating time available or has time left, the remaining normal operating time is considered to be used to produce additional vehicle Bs. However, if the target production volume of vehicle B cannot be completed in the normal operating time, overtime will be used, but only as needed, to meet the target production volume of vehicle B. And finally, if the target production volume of vehicle B cannot be met using the allotted overtime, the maximum amount of overtime is allocated to make the product and the total number of units produced is calculated.

First, time needed to make A is calculated from the effective production volume of A

$$EPV_{Ai} = \frac{TargetPV_{Ai}}{1 - RR_{Ai}}. \tag{2.12}$$

The total time needed to produce vehicle A is

$$T_{Ai} = EPV_{Ai} * CT_A * (1 + DT_{Ai}). \tag{2.13}$$

Therefore, the available time for producing vehicle B is

$$AT_{Bi} = NormOpTime - T_{Ai}. \tag{2.14}$$

To evaluate whether the available time is sufficient to make the target production volume of vehicle B for that period, the effective production volume of vehicle B is calculated from available time for production of vehicle B and its cycle time. That is compared to the effective production volume of vehicle B needed to meet the target. If the former is larger, it means that with the choice of cycle time, the production line will be able to meet the target production volume. If the latter is larger, then overtime operation is needed.

$$EPV_{Bi} = MAX\left(\frac{TargetPV_{Bi}}{1 - RR_{Bi}}, \frac{AT_{Bi}(1 - DT_{Bi})}{CT_{Bi}} * 3600\right) \tag{2.15}$$

Note that the second amount is multiplied by 3600 because CT has units of seconds, while AT has units of hours. The actual time needed to produce vehicle B is then

$$T_{Bi} = \frac{EPV_{Bi}}{CT_{Bi} * (1 - DT_{Bi})}. \tag{2.16}$$

Therefore, production volume of vehicle B is

$$PV_{Bi} = EPV_{Bi} * (1 - RR_{Bi}). \tag{2.17}$$

2.2.2 Cost Calculation

Now that all the model assumptions have been stated, the manufacturing cost can be calculated

Total manufacturing cost for period i consists of investment, material cost, and operating cost.

$$Cost_i = InvC_i + MatlC_i + OpC_i. \tag{2.18}$$

The operating cost can be further broken down to rework cost, energy cost, maintenance cost, and labor cost.

$$OpC_i = RWC_i + EnC_i + MaintC_i + LabC_i \tag{2.19}$$

Both energy and labor costs can also be broken down to those costs occurring during regular operations and overtime operations. In this model, however, the effect of manufacturing ramp-up decisions on manufacturing cost is considered. Therefore, any costs that are unaffected by manufacturing ramp-up can be omitted without impacting the results of this study. In this case, we assume that the regular operating time is fixed and that regular operation energy cost will be ignored. To simplify the model further, overtime labor and energy costs depend only on the amount of overtime, and hence are grouped together into a single overtime operation cost.

$$OTC_i = OTLabC_i + OTEnC_i \tag{2.20}$$

Therefore, in this model, the costs of interest for period i can be written as

$$Cost_i = InvC_i + MatlC_i + RWC_i + MaintC_i + OTC_i \tag{2.21}$$

Investment cost is calculated by amortizing the total investment of floor space, tooling, and equipment over the entire launch period

$$InvC_i = \sum_{l=1}^{3}\sum_{i=1}^{n}\frac{Inv_l}{(1+dr)^i} \tag{2.22}$$

where l = 1 for floor space, 2 for tooling, and 3 for equipment and dr is the discount rate per period.

The amount of overtime needed, OT, is

$$OT_i = T_{Bi} - AT_{Bi}\,. \tag{2.23}$$

Assuming a fixed unit rework cost C_{REWORK}, unit material cost C_{MATL}, maintenance cost per unit time C_{DT}, and overtime cost per unit time C_{OT}:

Rework cost:

$$RWC_i = \sum_{k=1}^{2} RWC_{ki} = \sum_{k=1}^{2} EPV_{ki} * RW_{ki} * C_{REWORK} \tag{2.24}$$

Material cost:

$$MatlC_i = \sum_{k=1}^{2} MatlC_{ki} = \sum_{k=1}^{2} EPV_{ki} * C_{MATL\,i} \tag{2.25}$$

Maintenance cost:

$$MaintC_i = \sum_{k=1}^{2} MaintC_{ki} = \sum_{k=1}^{2} T_{ki} * DT_{ki} * C_{DT} \tag{2.26}$$

Overtime cost:

$$OTC_i = OT_i * C_{OT} \tag{2.27}$$

where k denotes the product A and B.

To calculate effective production volume, downtime, and rework rate, the manufacturing errors and interruptions during manufacturing must be modeled. Thus, the concept of manufacturing event is introduced to represent the state that the system is not operating correctly. Each manufacturing event is caused by a defect in the product and can have consequences such as a rejected or reworked part, and a downtime. The probability that a manufacturing event occurs is dependent on cycle time; the shorter the cycle time, the higher the event probability. This is because it is assumed that workers can solve more events when they can devote more time to the problem.

2.2.3 Revenue Calculation

The revenue of period i is simply the sum of the products of price, P, and number of products sold for both new and old products, S

$$Rev_i = \sum_{k=1}^{2} S_{ki} * P_{ki} \tag{2.28}$$

where k represents the old and new products. Price, P, is a part of the reputation – product quality – demand model which will be discussed in 4.3. Price is modeled as a function of reputation, R, and production volume, PV, with an assumption that all products manufactured are sold,

$$\begin{aligned} S_i &= PV_i \\ P_{ki} &= P(R_i) \end{aligned}. \tag{2.29}$$

While the detailed discussion of product selling price will be in 4.3, it is worth mentioning that the more delayed the manufacturing launch is, the shorter the time the firm has to build the products until they are replaced by a new generation of product, creating less revenue. Furthermore, selling price might also decrease with time, reducing potential revenue.

2.3 Optimal Cycle Time Ramp-up Search

From the last section, the mathematical model of how the decision variable—cycle time—affects objective function—net revenue—has been discussed in details. However, the goal of constructing the model is to determine the optimal cycle time that will maximize net revenue of the product life cycle. While the model is divided into small periods of steady state operation even during product launch, the performances from previous periods directly impact the system state in the later period: the amount of experience at the start of period i depends on the experience from each period 1 through $i-1$. Since the cycle time choice in each period will dictate the amount of experience gathered in that period, this means that each cycle time choice from the previous period will influence the optimal cycle time choice for the current one. Therefore, this optimization problem is a path-dependent global optimization problem.

There are a wide range of methods available when it comes to solving a global optimization problem. However, due to the path-dependent nature of the problem, many of the methods do not guarantee the global optimality of their solutions. Other methods guarantee global maxima but are computationally expensive. In this dissertation, multiple dynamic programming repetitions are implemented due to the problem being relatively computationally inexpensive.

The underlying principal of multiple dynamic programming repetitions is to combine dynamic programming with a local search algorithm, essentially implementing dynamic programming with different initial conditions. In the case of cycle time strategy optimization, the two initial conditions are at two extremes: always running full speed and always running at the lowest speed throughout manufacturing launch. After the two solutions are obtained, they are compared. If they match, the solution is assumed a global maximum, if not, they are local maxima one of which can potentially be a global maximum. Additional initial condition in the middle of the two solutions is implemented to find if other maxima exist. All local maxima are compared to determine which one is the best.

2.4 Comparison between Metrics

To verify the performance difference between throughput and net revenue maximization, the model is run twice—each time optimizing on one of the metrics.

The weekly target production volumes of the obsolete product (A) and new product (B) are shown below. The learning statistics, probability of solving underlying problems given for each manufacturing event, $Pr_j(Solve|Event)$ is 0.15 and the probability of solving underlying problems as more products are produced, $Pr(Solve|Volume)$ is 0.01. The learning statistics apply solely to the production of vehicle B.

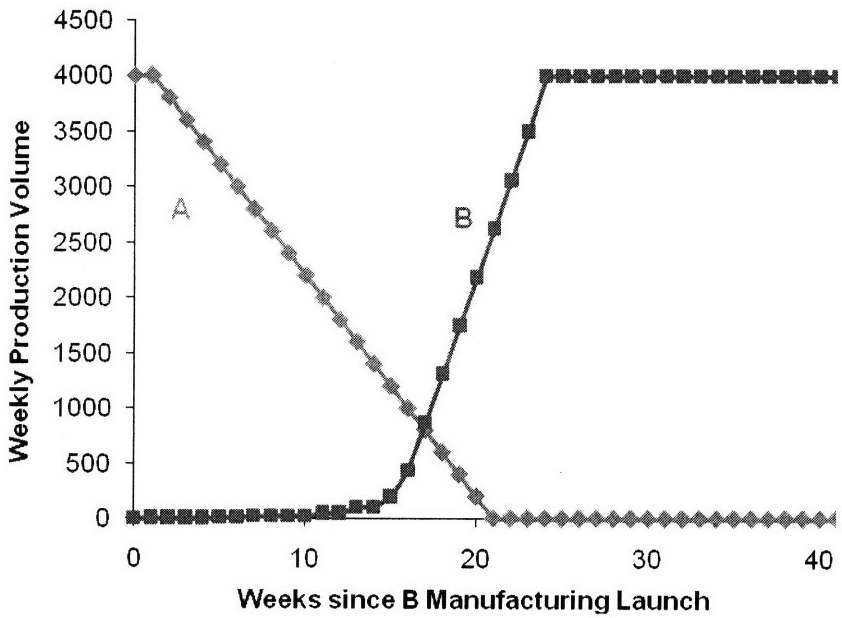

Figure 2-4: Weekly Target Production Volumes during Manufacturing Launch

Once the data shown in Figure 2-4 is input into the model and processed. The optimization result from maximizing throughput and net revenue is shown in Figure 2-5.

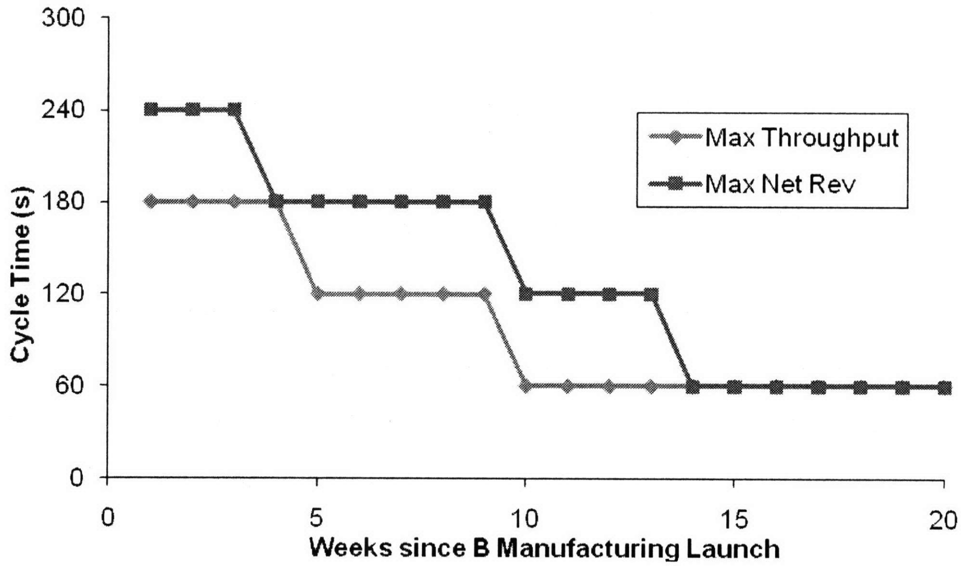

Figure 2-5: Comparison of Optimal Ramp-up Strategies for Throughput and Net Revenue

In Figure 2-5, the horizontal axis represents the time of after manufacturing launch in weeks, while the vertical axis represents the cycle time choice in seconds. By maximizing net revenue, the model suggests that manufacturing launch starts out with cycle time = 240 s (4 slots; 4*60 s = 240) for 3 weeks, speeding up to 180 s for 6 weeks, to 120 s for 4 weeks, and to full speed in week 14. On the other hand, maximizing throughput suggests that launch starts at 180 s for 4 weeks and speeding up to 120 s for 5 weeks, and finally to full speed in week 10.

Based on the optimal strategy results, to maximize net revenue the operator should ramp-up cycle time at a slower rate than to maximize throughput. The net revenue of the model using throughput maximization is $1,908,000, while that of the model using net revenue maximization is $1,990,000, which is approximately a 4% increase. The reason for this is shown below.

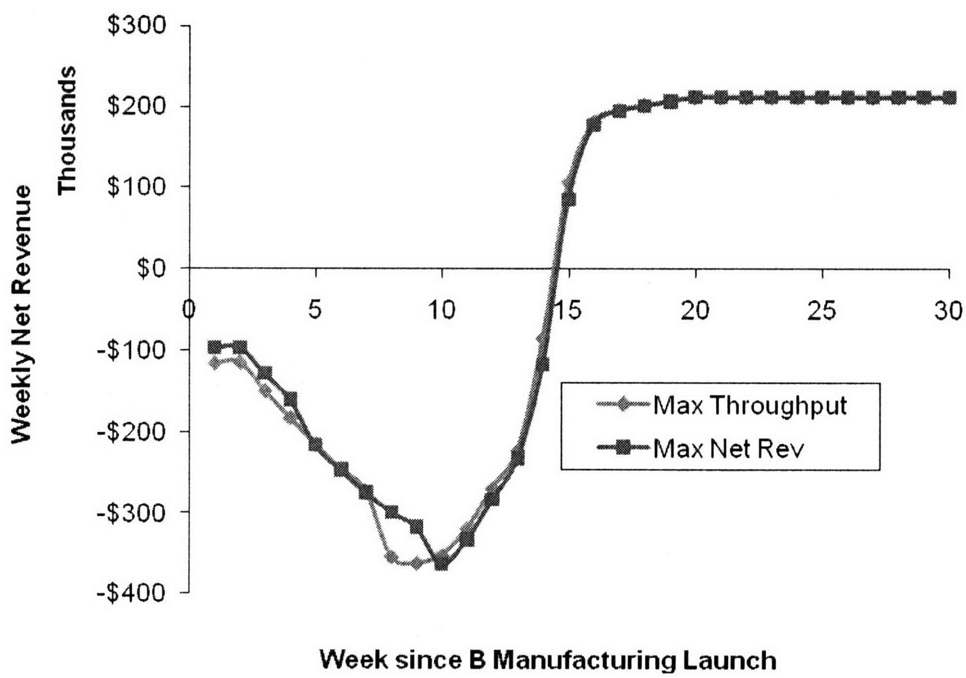

Figure 2-6: Weekly Net Revenue Comparison between Two Metrics

In Figure 2-6, again the horizontal axis represents the weeks since manufacturing launch, while the vertical represents the weekly net revenue as a result of cycle time choice in Figure 2-5. Slower cycle times at the beginning of launch helps the producer lower the amount of manufacturing events which results in correspondingly lower costs up into week 10, at which point both metrics suggest running at the same cycle time. Maximizing throughput causes the line to be run faster resulting in additional manufacturing events prior to week 10. While this is costly, it allows the line operator to gather more experience leading to fewer manufacturing events from week 10 on. Due to discount rate effect, however, the late cost saving does not offset the early cost increase. Therefore, net revenue maximization, which essentially suggests that the producer avoid early costs and even if that means delaying some forms of manufacturing learning results in an improved financial outcome.

To illustrate the benefit of using net revenue as opposed to throughput, sensitivity analysis of the performance difference is performed with respect to changes in learning rates and profit margins. In this analysis, the variation on learning rates is performed simultaneously on all types of manufacturing events. Recall equation (2.7), all $\Pr_j(Solve|Event)$ are set to the same value denoted by Pr on the plots.

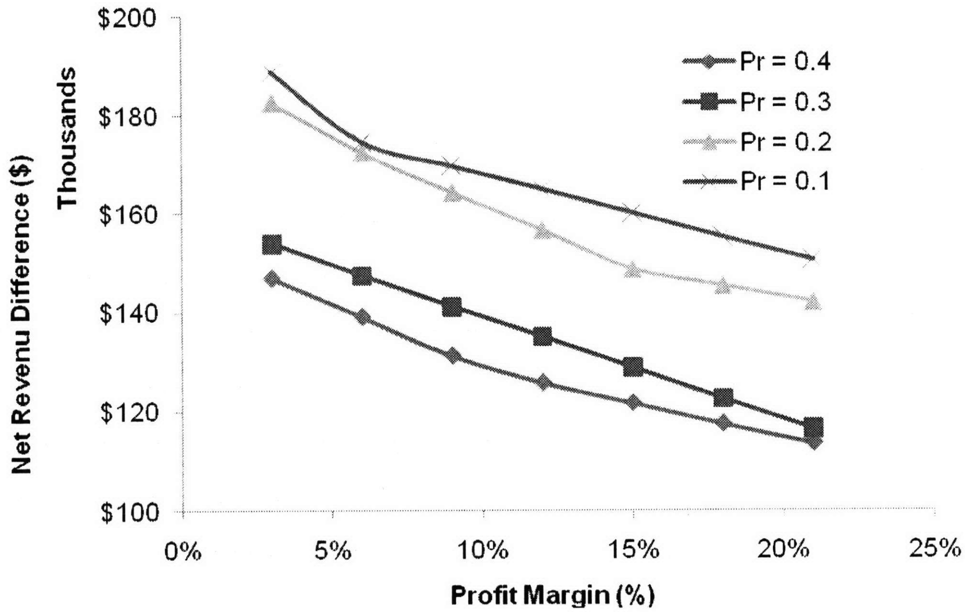

Figure 2-7: Net Revenue Difference under Different Profit Margins and Learning Rates

In Figure 2-7, the improvement in net revenue using net revenue maximization rather than throughput maximization is shown to be inversely proportional to product profit margin. This is because as profit margin grows, throughput becomes an increasingly accurate indicator of launch profitability. Net revenue difference is also inversely proportional to learning. Since higher rates of learning mean less frequent rework, rejects, and downtimes, the costs of which the throughput metric does not consider. As learning increases, these costs decrease and therefore the accuracy of the throughput as a proxy metric for launch profitability increases. Note that there are discontinuities in slopes of the net revenue difference. This is because, while throughput maximization always suggests the same cycle time ramp-up strategy regardless of profit margin, net revenue maximization suggests different ones. The higher the profit margin, the faster the cycle time ramp-up net revenue maximization suggests and the closer it is to that of throughput maximization. Faster ramp-up creates less difference between net revenue of the two metrics and therefore, smaller slope.

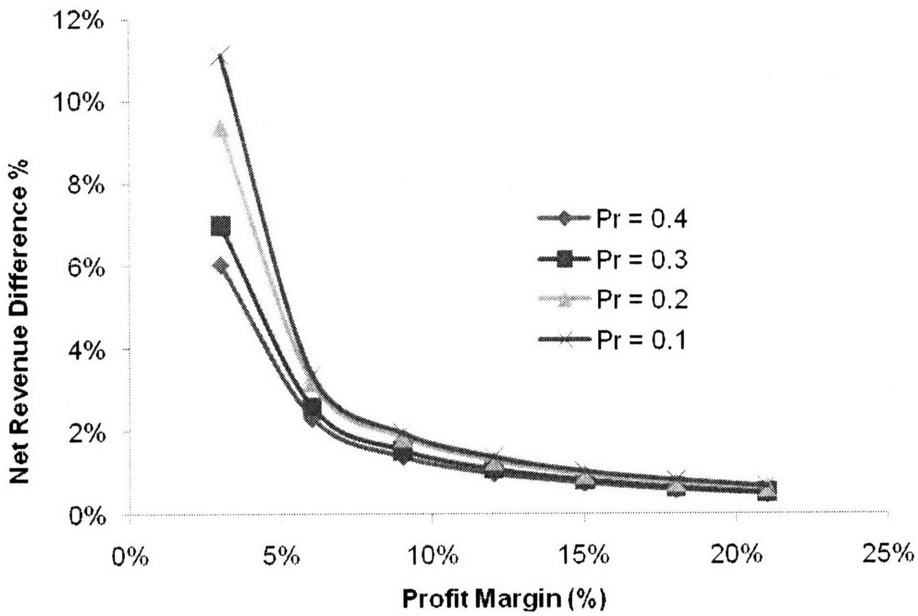

Figure 2-8: Net Revenue Difference % under different Profit Margins and Learning Rates

From Figure 2-8, the net revenue difference percentage, which is the ratio of net revenue difference and net revenue of the throughput metric case, is also inversely proportional to the learning and profit margin. However, the exponential shape of the curve is due to combination of the effects of the quantity of net revenue of throughput metric and the quantity of net revenue difference when the profit margin changes. For example, when profit margin decreases, the net revenue difference increases, but the net revenue of throughput metric decreases. Therefore, the net revenue difference—net revenue difference divided by the net revenue of throughput metric—grows exponentially.

While net revenue difference percentage may seem minimal especially for fast learning rates and high profit margins, it is quite significant under low profit margin and low learning rates. For example, an automotive firm producing high-volume, entry-level vehicles usually employs matured technologies (low learning rate) and sells them at 3% – 5% profit margin (de Weck, Suh et al. 2003). It would be possible for the firm to make as much as additional 10% net revenue from such products, which can be substantial.

2.5 Manufacturing Model Extension

Thus far, the net revenue model has the capability of evaluating the performance of manufacturing facility during manufacturing launch. It considers neither impact of product development nor customer reaction to product quality on net revenue and on the optimal manufacturing launch path. This section will discuss the extensions needed for the model to make that connection.

The first step towards extending the model is to identify the specific parameters within the net revenue model which should be impacted by product development and customer reaction to quality. The feature that is common to all of these activities is the issues/defects. Defects impact the manufacturing launch path through their impact on rework, rejects and downtimes and in turn through the costs that are affected by these variables. Defects also impact product quality and consequently customer reactions, which in turn impact willingness to pay, vehicle price and thus firm revenues. Finally, the number of issues, and therefore the number of issues are a function of the product development strategy. While the concept of linking these phases of a vehicle project life by tracking the impact of issues/defects is clear, representing the details of the interactive effects can be complicated.

2.5.1 Latent Issues

During product development after the prototype is built, the data on number of problems regarding various aspects of products are collected. In automotive industries, these are called latent issues, usually with the units of issues per thousand vehicles (IPTV). The number comes from a multitude of tests done on a few vehicles, which is then extrapolated to IPTV number. As product development progresses, this number gradually decreases, representing the improvement in the product design.

Although one would like to believe that this number would reduce to zero before the product design is transferred to be manufactured in a facility, this is not realistic in any complex product with a combinatorial number of potential failure modes. Due to the complexity of the product and the number of components in the final product, product development cannot progress until the product is completely issue-free. However, the product development duration decision does have a significant impact on the number of issues entering the manufacturing process as well as the final product quality. Thus, the issue is determining when to stop finding and solving problems.

Due to variations in product manufacturing, latent issues may exist in some products and not in others of the same product design. The issues that exist in a product are defects. Once in the manufacturing facility, defects can manifest themselves as manufacturing events. The higher the number of latent issues, the higher the probability of manufacturing events. Defects that caused manufacturing events are eliminated. However, while the defect itself is also remedied, only sometimes are the underlying causes discovered and fixed. Only after the root cause of a defect is solved will the defect be permanently eliminated from all subsequent products.

Some latent defects, however, will remain in the product without causing manufacturing events. These defects may manifest themselves after the product is subject to usage, thus impacting customer satisfaction and the reputation of the firm. The effects of latent issues on product development, manufacturing, and customer reaction are mapped in

Figure 2-9

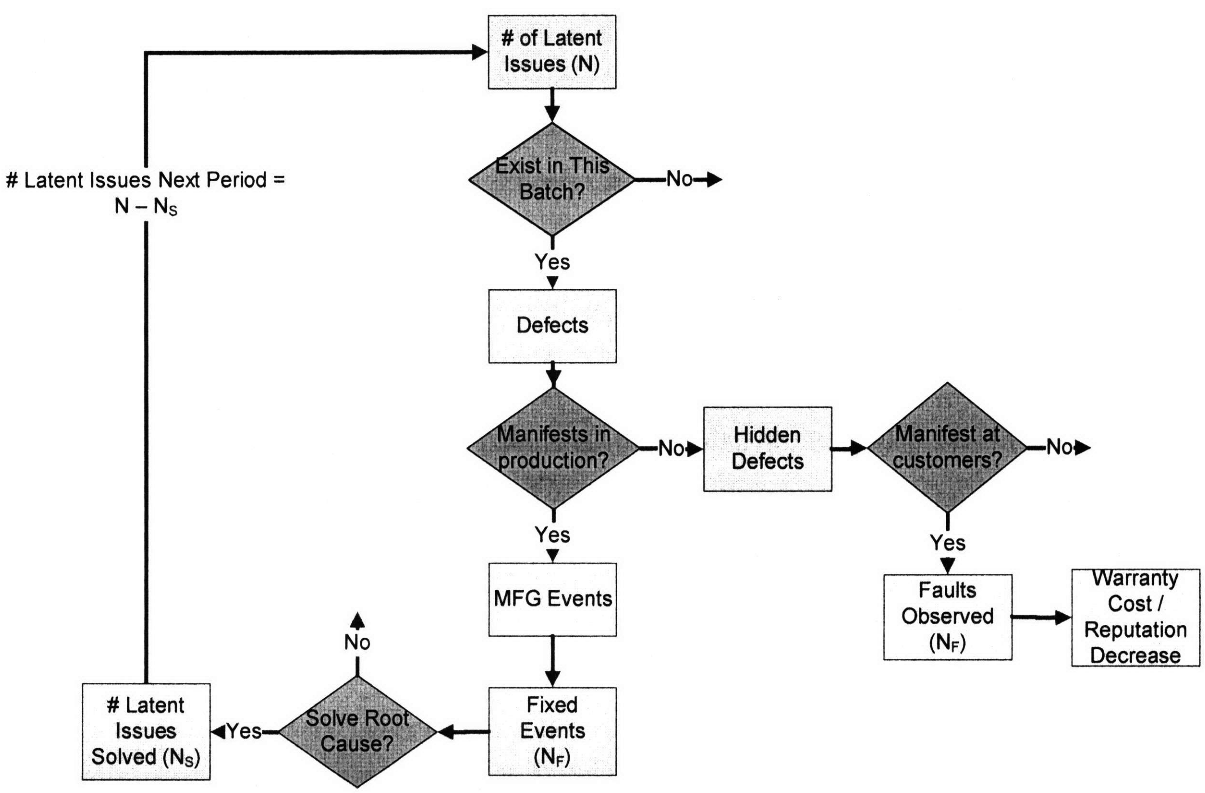

Figure 2-9: Latent Issues Manifestation and Elimination in Product Launch

2.5.2 Bridging Product Development and Manufacturing

Now that the effect of latent issues has been mapped out throughout a product lifecycle, the relationship between the amount of latent issues and its effect must be mathematically defined. In section 2.2.2, the model implicitly assumes that manufacturing events appear randomly with no underlying cause; through the concept of defects and their relationship to latent issues, manufacturing events can now be related to the product development strategy.

For each product in a manufacturing facility, latent issues that exist in it is are defined as defects, therefore the number of defects per product in the first week of manufacturing is

$$d_1 = \Pr(issues \rightarrow defects) * N_1. \qquad (2.30)$$

where N_1 is the latent issues at manufacturing launch (period 1). Since only a fraction of latent issues are inherited as defects in each product, it is impossible for the ones that are not present to be eliminated from the product design. Therefore, the defect elimination process through learning in equation (2.7) becomes

$$N_{i+1} = N_i - \sum_j \Pr_j(Solve \mid Event) * \#event_{ji} - \Pr(Solve \mid Volume) * PV_i. \qquad (2.31)$$

where N_i is the number of latent issues in period i. And for each period i, the number of defects per product becomes

$$d_i = \Pr(issues \rightarrow defects) * N_i \qquad (2.32)$$

2.5.3 Bridging Manufacturing and Product Quality

When a manufacturing event interrupts a process, the station is temporarily shut down and attending workers investigate and solve the event. The model assumes that after the event is eliminated, so is the defect that causes the event. Therefore, the number of defects left in the finished product is

$$d_{fi} = d_i - events \qquad (2.33)$$

The defects eliminated are specific only to the one product that causes manufacturing event, which means the same defect in other products can still cause an event. However, there is a probability that the workers or supervisors investigate the problem, understand the root cause, and make changes to the original product design so that the defect is permanently eliminated from all subsequent products. Indeed, subject to resource constraints, this is common practice during product launches.

The number of defects in the finished product is an indicator of product quality, which directly influences reputation of the firm and therefore the demand for the product. The product quality will also determine the number of product failure and therefore the warranty cost incurred to the firm.

On the cost side, warranty is the cost incurred to the manufacturing firm when the purchased products fail, needing repairs or part replacements. The number of product failures, or faults, of a product manufactured in period i over the warranty period is directly proportional to the number of defects in finished product and failure rate function.

$$F_i = F(d_{fi}, b) \tag{2.34}$$

where b is the failure rate function. By assuming that all faults have an average servicing/part replacement cost, C_{WARR}, the warranty cost per period of manufacturing in period i is

$$WarrantyC_i = C_{WARR} * F_i * PV_i \tag{2.35}$$

Therefore, the total cost per period equation (2.18) becomes

$$Cost_i = InvC_i + MatlC_i + OpC_i + WarrantyC_i \tag{2.36}$$

On the revenue side, finished product quality in each period will influence the firm reputation, and the product selling price is influenced by the reputation.

$$\begin{aligned} R_i &= R(d_{fi}) \\ P_{ki} &= P_k(R_i) \end{aligned} \tag{2.37}$$

Therefore, the total revenue for manufacturing period i is

$$Rev_i = \sum_{k=1}^{2} P_{ki} * PV_{ki} \tag{2.38}$$

Both reputation and warranty will influence the net revenue, the metric for product launch performance. Incorporating these effects into the model will have an impact on the decisions. The relationship between them will be discussed in details in Chapter 4.

3 Product Development Model

Now that the number of latent issues has been identified as the connection between product development and manufacturing, the relationship between product development duration and its relationship to latent issues will be explored.

While the scope of product development as defined in the literature usually involves "the transformation of a market opportunity and a set of assumptions of product technology into a product available for sale," (Krishnan and Ulrich 2001) in this dissertation, product development is the process in which the product concepts are developed, tested, and validated, but before the product goes through manufacturing launch process. This includes the process of building prototypes to verify concepts and manufacturing processes, which usually takes place on different facilities than the intended production line.

The number of latent issues indicates the amount of problems on a product design that has yet to be fixed. In the beginning of a project, a product design has a multitude of requirements it has to satisfy. As product development progresses, reworks are made to the original design to correct part requirements or to accommodate new ones from downstream activities, solving latent issues.

Assuming that the number of engineers on a product development project is constant, product development duration will have implications on cost and performance. A short product development duration allows for inexpensive product development and faster release of the product, allowing that product to capture more of the market and provide an earlier revenue stream, albeit at the cost of having a lower product quality, and vice versa. To fully understand the tradeoff within product development itself and its implication on product launch as a whole, a model of the relationship between duration, cost, and product quality is needed.

Browning et al. (2006) provided an excellent review of various modeling concepts of the process of resource management, scheduling, and sequencing of product development activities. Some of the most important methods are PERT/CPM (Project evaluation and review technique/critical path method) and DSM (design structure matrix). These methods share the same principle of modeling product development as a network of activities. PERT/CPM maps out all the dependence between activities, along with the duration required for the task. The critical path is then determined by the longest path from the beginning to finish. Activities not on the critical path are called 'floating' and can be delayed without affecting the project duration. PERT/CPM, however, cannot model rework generated by other activities.

The literature review on product development modeling indicates that DSM is a mathematically rigorous method of modeling product development duration, latent issue elimination, and cost. DSM has been used extensively in various industries such as the pharmaceutical, automotive, and semiconductor industries. (Eppinger, Whitney et al. 1991; Smith and Eppinger 1997; Sullivan, Griswold et al. 2001; Browning and Eppinger 2002; Yassine and Braha 2003) Throughout this chapter, the background of DSM, its application to product launch model, and the effect of integrating product development consideration into product launch decisions will be discussed.

3.1 Design Structure Matrix Modeling

The design structure matrix (DSM) approach has been used extensively to model the cost and product development duration of product development activities. A DSM displays the relationships between interdependent components of a system using matrix representation for easy interpretation and analysis. A DSM is a square matrix with identical row and column labels. In Figure 3-1, elements are represented by the shaded elements along the diagonal. An off-diagonal mark signifies the dependency of one element on another. For example, entry (row A, column B) shows that element A is dependent on information from element B, and entry (row E, column A) shows that element E is dependent on information from element A.

	A	B	C	D	E
Element A		0.2			
Element B	0.4		0.4		0.7
Element C				0.1	
Element D		0.5			
Element E	0.2			0.9	

Figure 3-1: Example DSM

According to a review by Browning (2001), there are mainly two categories of DSMs: static and time-based. Static DSMs represent system elements existing simultaneously, such as components of product architecture or groups in an organization. In time-based DSMs, the ordering of the rows and columns indicates a flow through time: upstream activities in a process precede downstream activities.

Static DSMs can be further broken down into component-based and team-based. Component based DSMs are used to model system architectures based on components and their relationships. Team-based DSMs are used to model organization structures based on groups and their interactions.

Time-based DSMs can also be broken down into activity-based and parameter-based. Activity-based DSMs are used to model processes and activity networks based on activities, information flows, and their dependencies. Parameter-based DSMs are used to model low-level design decisions and parameters, systems of equations, subroutine parameter exchange, etc.

Since the implications of product development duration on product development cost and performance are to be modeled, an activity-based DSM is employed. However, activity-based DSMs are mainly used to predict the cost and duration of product development without any indication of performance. Therefore, modifications to normal DSM methods are made so that it can predict the performance as well.

3.1.1 Activity-based DSM

In this type of DSM, the product development process is broken down into various activities. Model entries represent the information dependence between activities. The duration of an activity is used to model uncertainty and complexity of the activity. Precedence is used to determine relative priority of the activities. Iterations are modeled to predict the patterns of work progression and rework based on the exchange of information between activities.

3.1.1.1 Activity Duration

The model uses the triangular probability distribution to represent the characteristic of activity duration. For each activity, there are three estimated durations—optimistic, most likely, and pessimistic—for the duration of one execution. The duration is the time between the start and end of the activity—even though the activity may iterate more than once afterwards. Once the activity needs rework, its duration decreases with each rework. The model uses the Latin Hypercube Sampling (LHS) method to incorporate the uncertainty of the expected duration of an activity based on the three estimated durations. (Cho and Eppinger 2001) Using the optimistic and pessimistic values as two extremes for the distribution, the sampling algorithm divides the range between them into *N* pieces of equal probability. The algorithm then randomly samples the duration from the pieces.

3.1.1.2 Precedence Constraints

It is assumed that the information flow between activities occurs either at the beginning or at the end of an activity. Based on this observation, the information flow can be defined as the case that the activity requires final output information from the upstream activity to begin its work. It is translated to a "finish-to-start" precedence constraint between two activities.

The DSM is used to document these information flows and precedence constraints by having the most upstream activity in the first entry, followed by other downstream ones until the last activity. In the precedence constraints matrix entries, $PC(i, j) = 0$ if activity j does not need information from activity i, and 1 if it does.

3.1.1.3 Iteration

Cho and Eppinger (2001) defined iteration as the repetition of activities to improve the development process. Here, iteration is referred to as rework caused by other activities without including repetitive work within a single activity. The model assumes that planned rework of an activity is generated due to: (1) change of inputs when other activities are reworked or (2) failure to meet the established criteria.

To generate iterations, the model uses rework probability, rework impact and the learning curve. Rework probability is a measure of the chance that an activity generates rework. $RP(i, j)$ represents the probability that activity i does rework because of the failure of activity j for $i, j = 1, \ldots, n$. In the case of $i < j$, it represents the feedback rework; failure of downstream activity j caused the rework in upstream activity i. In the case of $i > j$, it represents the feedforward rework; downstream activity i needs to do since upstream activity j has generated new information after it has reworked.

Rework impact is a measure of the strength of dependency between activities. $RI(i, j)$ represents the percentage of activity i to be reworked when rework is caused by activity j for $i, j = 1, \ldots, n$. Rework impact is assumed to be constant in each iteration.

The learning curve represents the improvement of activity duration and cost when it repeats. It represents the percentage of the duration or cost from kth time when activity i reworks for the k+1th time. The model assumes that the activity duration and cost decrease in each repetition until it reaches the minimum percentage of original duration when activity i does the same work repeatedly. Thus, rework amount is calculated as the original duration multiplied by the rework impact and learning curve to the power of the number of repeats (with a preset minimum). Figure 3-2 shows the rework probability and impact for sequential iteration using the DSM representation, and Figure 3-3 illustrates the learning curve.

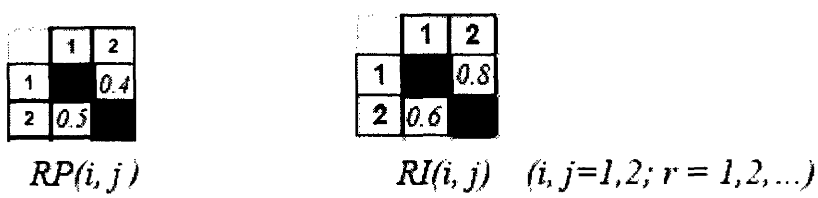

Figure 3-2: Rework Probability and Impact Matrices. (Cho and Eppinger 2001)

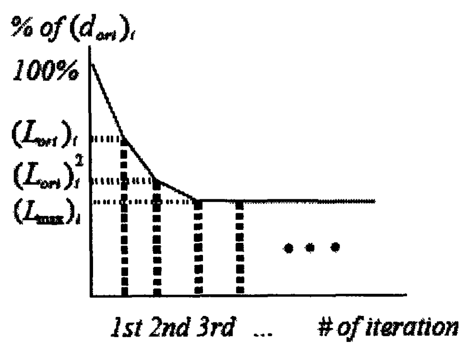

Figure 3-3: Learning Curve Effect on Activity Duration. (Cho and Eppinger 2001)

Now that DSM activity durations and costs and rework generation mechanism required to calculate reworks during product development have been defined, DSM discrete event simulation can be utilized to generate product development duration and cost.

3.1.2 DSM Simulation

In DSM discrete event simulation, events trigger state transitions and time advances in discrete steps by the time elapsed between events. The model uses different activity distribution in each simulation run which are initially sampled using the Latin Hypercube Sampling method. (Cho and Eppinger 2001) With these activity durations, it determines the first state transition (first activity to finish from the last state) and calculate the additional duration, after which it generates the next state by scanning all activities for required reworks and determines the active activities. It assumes that an activity can begin to work as early as possible when it has all the necessary inputs from upstream activities.

In this model, a state transition is triggered by the completion of an activity. Thus, when any active activity in the current state q is completed, the model makes a transition to the next state $q+1$. The duration of state q ($q = 0, 1, 2, \ldots$) is defined as the minimum remaining duration of active activities in the state. Before making the transition, the model subtracts the duration of the current state from the remaining durations of all active activities. If all the remaining activities are completed (remaining durations are all zero), a simulation run is complete and the product development duration is calculated as the sum of all durations. After a user-defined number of simulation runs, the probability distribution of product development duration and cost can be displayed.

The simulation steps follow closely the work by Cho and Eppinger (2001), which can be summarized as follow:

Step 1: Model sets initial conditions, setting all activities to incomplete.

Step 2: Start unfinished activities that has all information needed from upstream activities.

Step 3: Sample the activity cost and time.

Step 4: When activity in progress is finished, add activity cost and duration to the total values and generate rework impact on other activities based on rework probability matrix.

Step 5: Repeat 2-4 until termination conditions are met.

Step 6: Report activity cost.

The termination condition is set to the completion of all activities. The simulation can then report the distribution of cost and duration when product development is completed.

3.2 Quantifying Product Development Performance and Cost

In section 2.5, the extension of manufacturing model to include product development and product quality is discussed. In particular, the number of latent issues is used as a connection between product development and manufacturing. The number of reworks is chosen as a DSM model output to represent the number of latent issues because of the difficulty with directly modeling the number of latent issues during product development.

Direct testing for latent issues can be an expensive, difficult and time consuming process, especially for complex product designs with multiple components. Therefore, the information may not always be readily available throughout different periods in product development. Number of reworks, on the other hand, can be easily modeled and generated throughout product development. It is also a reasonable indicator of latent issues because every time a rework occurs, it is assumed that some latent issues are eliminated—a hypothesis that will be proven in section 3.2.2.

In modeling and predicting product development duration and cost, activity-based DSM discrete event simulation generates the results based on activity cost and duration distributions. The simulation proceeds until all activities are completed, signifying that all latent issues are solved.

By itself, the process of latent issues elimination during product development may continue until all issues are eliminated. However, market pressure and scheduling problems may force the product development process to be finished early at a set time rather than until its completion. To model the duration limit, some modifications in simulation algorithm have to be altered.

3.2.1 Modifications to DSM Simulation

The modification is on the termination conditions of the simulation. In the all previous works regarding DSM simulation, the termination condition is that all activities are completed, since DSM simulation was utilized mainly to predict the duration and total cost of product development. In this model, the termination condition is a product development duration limit, since we would like to get an insight on how the decision variable—product development duration—affects the outputs of interest—product development cost and performance (number of latent issues). The simulation is also allowed to run until completion once to measure the total rework needed. Once the time counter reaches a specified duration, the simulation is forced to stop. In addition to the modified termination conditions, a new feature is added into the simulation step 4 to count the number of rework events. The modified simulation steps are:

Step 1: Model sets initial conditions, setting all activities to incomplete. Number of rework events = 0.

Step 2: Start the earliest unfinished activity.

Step 3: Sample the activity cost and time.

Step 4: When activity in progress is finished, add activity cost and duration to the total values and generate rework impact on other activities based on rework probability matrix.

Step 5: Number of rework events increases by 1.

Step 6: Repeat 2-5 until termination conditions are met.

Step 7: Report activity cost.

Basically, every time an activity is finished, the rework counter number goes up by 1. The termination condition changes from product development duration = 20, 40, …, 580 days. At the end of the simulation, the model reports both the accumulated activity cost and number of rework events. Because this is a simulation, it has to be run for several repetitions in order to predict reliable results. Therefore, the number of rework events is the average over the total number of simulation runs. The difference between the number of total rework events needed and the number of rework events at any duration is called latent rework events. Figure 3-4 shows the average number of latent rework events over 5000 repetitions for different product development durations.

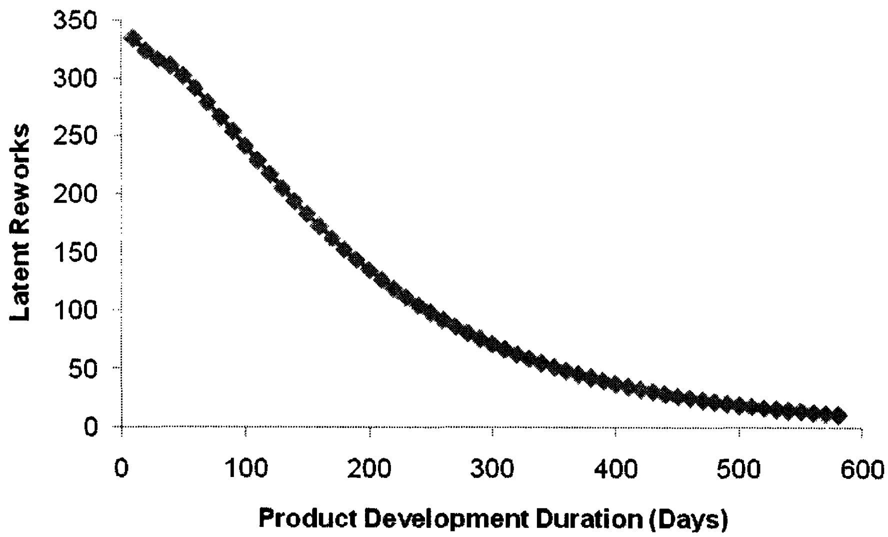

Figure 3-4: Average Number of Latent and Product Development Duration

3.2.2 Establishing Duration – Latent Issues – Cost Relationship

To show that the number of rework events is a good modeling proxy for the number of latent issues, a correlation between these factors must be established. A correlation test between the number of rework events generated from DSM simulation and latent issues data during product development using time-series data of number of latent issues of a midsize vehicle launch program was conducted. This data is presented in Figure 3-5. It is important to note that the product development duration = 0 does not correspond to the actual beginning of the concept design of the product; it actually corresponds to the first time the number of latent issues in product design is tracked through integration testing and thus most closely corresponds to the completion of first integrated prototype.

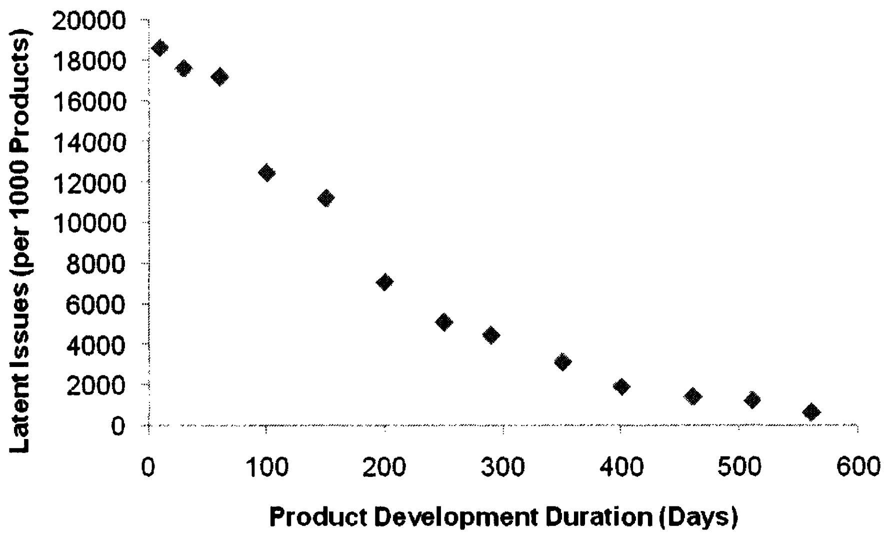

Figure 3-5: Number of Latent Issues (per 1000 Products) of a Midsize Vehicle Program during Product Development

Using linear regression, the result also shows a linear relationship between the number of rework events and latent issues.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.940221752
R Square	0.910834682
Adjusted R Square	0.877501349
Standard Error	953.8186818
Observations	13

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0	#N/A	#N/A	#N/A
X Variable 1	56.07780334	3.268337229	17.1579	8.28E-10

Figure 3-6: Latent Issues – Number of Rework Events Linear Regression Result

The regression result in Figure 3-6 shows a strong correlation between latent issues and number of events with high R-square value and good t-statistics. Since t-statistics represent the ratio of standard errors to the coefficient of the regression, large t-statistics show that the curve fitting is highly accurate. From this result, a linear equation between the latent rework events and latent issues can be written as

$$Latent\ Issues(t) = k * \#latent\ rework(t) . \qquad (3.1)$$

where k is the average number of latent issues solved for each rework. In this case, Equation (3.1) becomes

$$Latent\ Issues(t) = 56 * \#latent\ rework(t) \tag{3.2}$$

The DSM model can also report the cumulative cost at each product development duration. The result is illustrated below

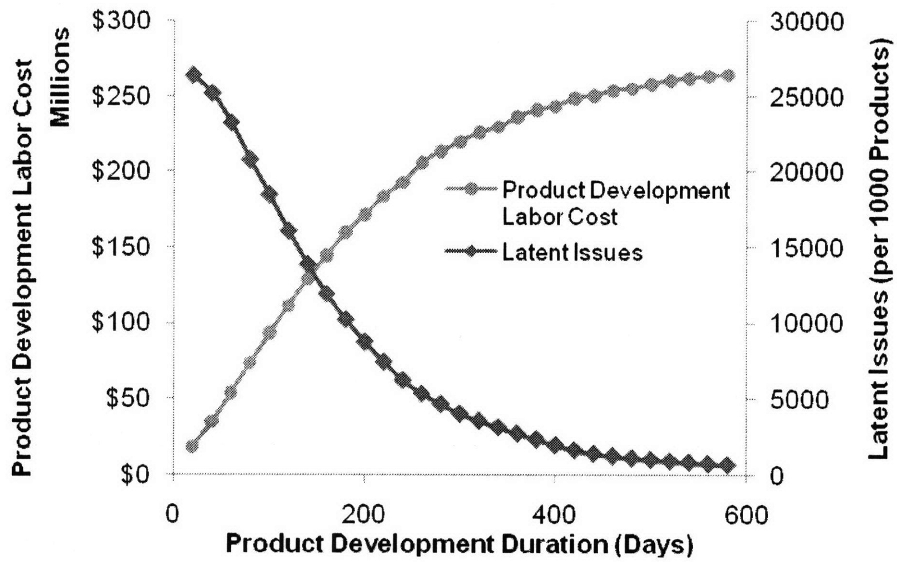

Figure 3-7: Product Development Labor Cost, Latent Issues, and Product Development Duration

As illustrated in Figure 3-7, determining the duration of the product development activities involves a tradeoff between the product development cost and the number of latent issues. This relationship is the basis for understanding the impacts of varying product development duration on both manufacturing costs and eventual product quality, warranty and reputation. Having a method that fully quantifies these tradeoffs is essential.

3.3 Linking Product Development and Manufacturing

The extension to manufacturing model and how latent issues from product development affect manufacturing has been discussed in section 2.5. Furthermore, the relationship between product development cost, latent issues, and product development duration has also been established in the previous section. These two modeling approaches can be combined in order to be able to explore the affects of product development duration on net revenue considering both the cost incurred during product development and the impacts on manufacturing costs during ramp-up.

The product development cost will directly affect net revenue calculation by increasing the cost: the longer the duration, the higher the cost, as shown in Figure 3-7.

The importance of product development costs is also magnified by the time value effect—since product development is the first process of product launch, the cost incurred here is more important than costs that occur later. This will lead to a faster product development to save product development cost. However, faster product development leads to higher latent issues at the beginning of manufacturing which will drive up manufacturing cost. Therefore, the latent issues effect will lead to slower product development duration to save manufacturing cost. These two tensions will create an optimal duration at which the increases in product development cost and manufacturing cost balance out.

There is also an issue of time value of cash flow involved when integrating product development into product launch. With the manufacturing model alone, cash flow amortization takes the beginning of product launch as the first day of manufacturing launch. With a new assumption that manufacturing launch starts immediately after product development is finished, however, different product development durations will lead to different manufacturing launch dates. This will lead to a biased comparison favoring longer product development durations because of a false assumption of time of cash flow. From this point on, therefore, the reference time for comparing net present value of net revenue is the beginning of product development.

Due to this reason, the net revenue calculation must now take into account the shift in reference time and additional product development cost, so equation (2.1) becomes

$$
\begin{aligned}
&NPV_{PD}(NetRev) = \sum_{i=1}^{n} \frac{NetRev_i}{(1+dr)^{i+c}} = \frac{1}{(1+dr)^c} NPV(NetRev) \\
&c = \frac{PD\ duration}{Period\ duration}
\end{aligned}
\tag{3.3}
$$

Essentially, each net revenue stream from period i is amortized as if it is from period $i + c$, where c is the amount of periods shifted by the product development duration.

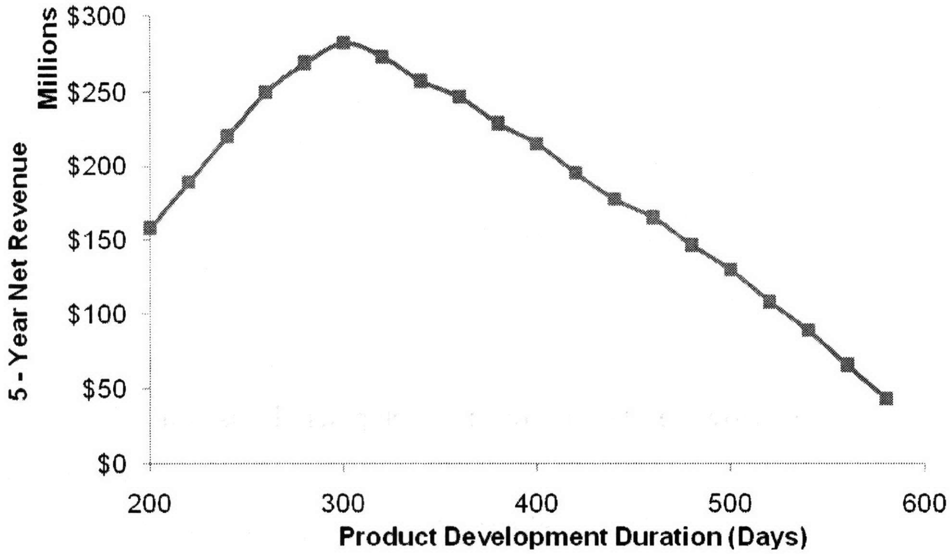

Figure 3-8: Product Launch Net Revenue versus Product Development Duration

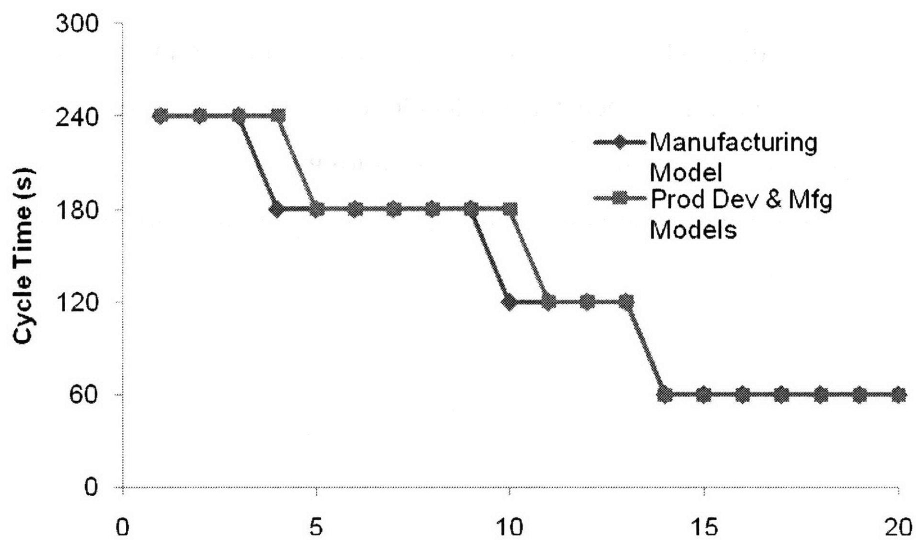

Figure 3-9: Optimal Cycle Time Ramp-up when Product Development Duration = 300 Days

Figure 3-8 shows the relationship between the total 5 year net revenue and the product development duration. The optimal product development duration is 300 days. It is important to note that the net revenue value plotted is corresponding to the optimal ramp-up for each duration. The maximum net revenue is $283 million. Shorter product development duration increase the revenue by the effect of time value of money and manufacturing and selling more products but suffer even more additional warranty cost, resulting in lower net revenue. Longer product development results in decreased warranty cost, but suffers from shorter manufacturing time and time value of money.

Figure 3-9 shows the corresponding optimal cycle time ramp-up for product development duration = 300 days compared with the optimal ramp-up without considering product development. When considering only manufacturing cost alone, the cycle time in the first week at 240 s and stays constant for 4 weeks. In week 5, the cycle time speeds up to 180 s, and stays there for 5 weeks. It speeds up again to 120 s in week 11, staying there for 3 week until reaching full speed in week 14. However, with the consideration of product development cost, the cycle time stays at 240 s for 5 weeks, and at 180 s for 6 weeks. It is important to note that in the manufacturing model only case, the number of latent issues input was assumed to be the same as the number of latent issues that would remain after a 300 day product development duration (4 issues per product) so that both cases have the same number of latent issues at manufacturing launch. However, explicit consideration of product development activities leads to different ramp-up strategies even with the same amount of latent issues at manufacturing launch, learning rates, product price, and costs (other than manufacturing cost). This is because the inclusion of product development cost increases the tension on the cost side and pushing the system to run slower to avoid high manufacturing cost at the beginning of manufacturing launch.

4 Customer Reaction to Product Quality

Product development and production launch strategies are not just about balancing the costs in these two activities, but also about considering their impact on final product quality and the resulting market acceptance of the product and the reputation of the firm and its effect on later products. Chapters 2 and 3, the production launch model and its extension to product development/DSM modeling, deal mainly with the interaction between the cost and product quality up to the time it is manufactured; the effect of product quality on cash flow once the manufacturing is finished has not yet been taken into consideration. Up to this point, the underlying assumption has been that regardless of product quality, all products made can be sold at a set price and do not incur extra cost.

While this assumption helps simplify the model and allows for easier results validation, it is highly unrealistic. Products do break down and require service after they are sold, and the demand and price a customer is willing to pay for the product depends highly on the product quality. In this chapter, the cost and value of product quality after the product is sold is explored.

4.1 Quantifying Product Quality at Customer

In typical customer reaction models, product quality is the quantity that measures the satisfaction of the customer about the product and affects the cash flows during the lifecycle of the product. The number of latent issues has been used to assess the product quality throughout different phases of product launch. However, for the customer, the notion of product quality differs slightly from the idea of product quality during product development and manufacturing. Here, it is a more physical concept: something a customer is able to observe. During product development and manufacturing, latent issues/defects are potential problems which may manifest themselves; in finished products, potential problems do not affect customer satisfaction as long as the customer cannot observe them. This notion of product quality has been used in automotive review magazines such as The Consumer Reports where the product failure rate is observed.

There may be other aspects of product quality that affects the customer satisfaction such as added features or aesthetically pleasing designs. The cost of these aspects, however, cannot be easily associated with the product launch decisions considered in this work, such as product development duration and manufacturing ramp-up. It is difficult to approximate the change in customer reaction, the additional cost, and the additional duration an extra feature would incur. Therefore, the notion of product quality in this dissertation will reflect the failure rate of the product.

There are multiple works available on modeling the failure rate of a product; most of these are warranty cost model studies where a failure rate is established to calculate the total amount of expected failures during a warranty period to estimate costs. The most prevalent failure rate distributions in the literature are exponential and Weibull distribution. These function forms are provided in equation (4.1).

$$b(t) = \begin{cases} k & \text{Exponential} \\ \dfrac{k}{\lambda}\left(\dfrac{t}{\lambda}\right)^{k-1} & \text{Weibull} \end{cases} \tag{4.1}$$

where $b(t)$ is the failure rate according to the distribution function.

An exponential distribution uses a constant rate of failure, usually associated with randomly occurring failures. A Weibull distribution is normally used because of its flexibility; its shape and scale varies with two parameters, λ and k. The shape, in particular, is controlled by k. If $k > 1$, the failure rate is monotonously increasing with respect to time, signifying failures associated with aging and wear. If $k = 1$, the failure rate is constant, and the distribution becomes the exponential distribution. If $k < 1$, the failure rate is monotonously decreasing with time, signifying an infant mortality behavior of failure. The scale parameter, λ, controls the relative spread of the distribution: the bigger λ is, the more spread out the distribution becomes.

Due to its flexibility and overall being the most prevalent throughout the literature, Weibull distribution will be used to model the rate of product failure that the customer can observe.

If all hidden defects are assumed to have the same rate of failure, and that a fault is caused by only one hidden defect (no compounded fault), then the failure rate of a product containing d defects is

$$b(t) = d\frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} \tag{4.2}$$

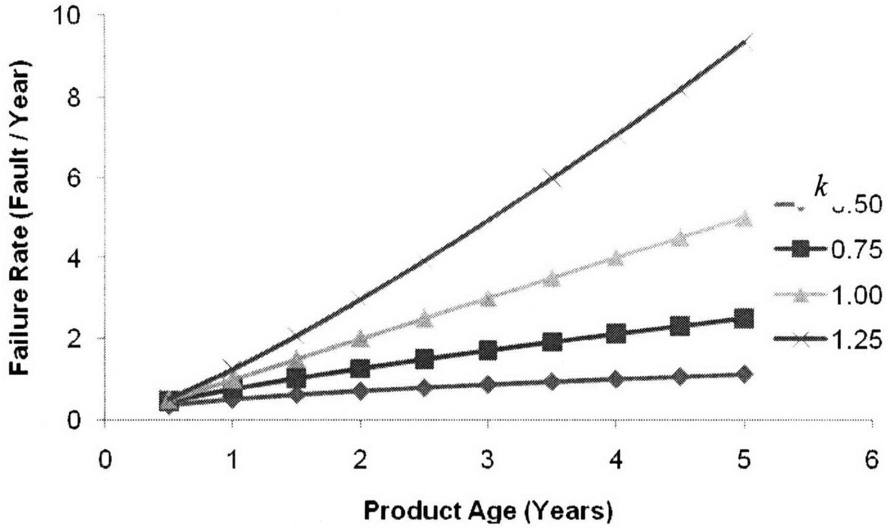

Figure 4-1: Weibull Distribution of Failure Rate for Various k when $\lambda = 1$

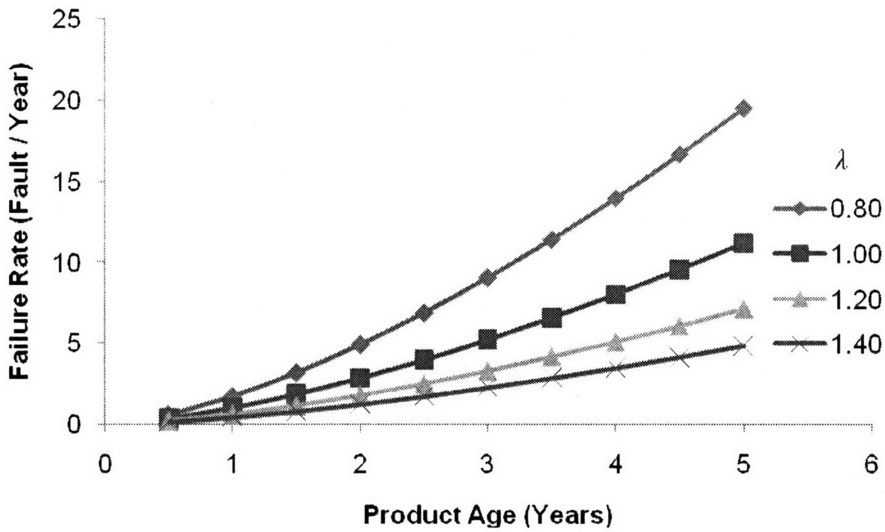

Figure 4-2: Weibull Distribution of Failure Rate for Various λ when $k = 1.5$

Figure 4-1 shows the effect of k on the Weibull distribution failure rate. When $k<1$, the failure rate slope is decreasing with time, when $k=1$, the failure rate slope is constant, and when $k>1$, the slope is increasing. Figure 4-2 shows the effect of λ on the Weibull distribution failure rate: the smaller λ is, the faster the failure rate increases. It is found Weibull distribution with $k = 1.5$ and $\lambda = 1$ fit the automotive failure rate data well, generating approximately 5 faults over 5 year period. (Lawless 1998) These parameters will be used for subsequent analyses.

Now that the quantity that represents product quality to customers is modeled from defects in finished products, it will be used to model the effects of warranty and reputation.

4.2 Warranty Cost Model

Warranty costs are directly related to the number of failures observed in the vehicle during the warranty period. This can be calculated as the integral of the failure rate over the warranty period. Applying the Weibull distribution from equation 4.2 for the failure rate of a product with d defects, the expected number of failures over time T is simply the,

$$E(\#\,Faults) = \int_0^T b(t)dt = d\left(\frac{T}{\lambda}\right)^k \tag{4.3}$$

where T is the warranty period. It is important to note that while not all faults are covered by warranty, all faults affect customer perception and the firm's reputation.

Figure 4-3: Expected number of faults over product age when $d = 0.6$, $k = 1.5$, and $\lambda = 1$

Figure 4-3 shows the accumulated number of faults with respect to product age. This result is consistent with automotive industry data. In reality, each fault has a different cost associated with it. To keep the model simplified, however, all faults are assumed to have the same warranty cost.

$$WarrantyCost = c * E(\#\,Faults) \tag{4.4}$$

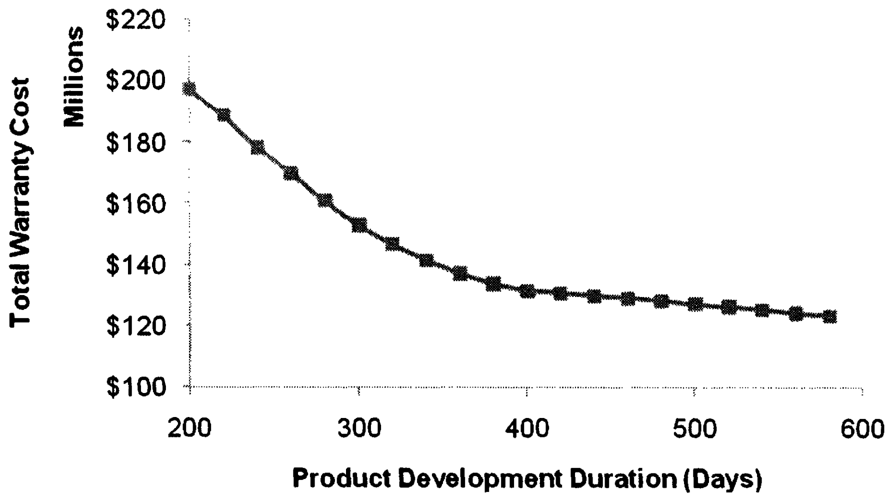

Figure 4-4: Total Warranty Cost over Product Lifecycle as a Function of Product Development Duration

Figure 4-4 shows the total warranty cost for all products sold over the lifecycle (5 years) is decreasing when product development duration is longer. It is this additional cost that extends the optimal product development duration when warranty cost is considered. Note that the rate of warranty cost reduction is slowing after 400 days because the rate of latent issues elimination in product development past 400 days is low; there are small amount of latent issues to be dealt with and therefore small amount of issues to be eliminated. It is also important to note that the total warranty cost is slightly smaller than net revenue shown in Figure 3-8. Since Warranty Week claims warranty cost is ~2.5% total revenue (Arnum 2006), while the model assumes 3% profit margin with warranty included, the assumption that the $100 warranty cost per claim is consistent with industry data.

4.3 Reputation Model

Up until this point, the model has been addressing the effects of product development duration and manufacturing ramp-up to product quality, cost, and revenue, yet the effect of product quality on revenue has not been addressed. Revenue has always been part of the equation to calculate net revenue, but it stays constant regardless of product quality. However, product quality also impacts the market for the vehicle and thus its sales volume and selling price, in other words, the firm's revenue.

While customer demand for a product depends highly on the product quality, the notion of quality can be difficult to perceive in some products. In this case, customers rely on reputation as a signal for product quality. Customers trust that a firm with a reputation for producing high quality products will in fact continue to manufacture high quality products. These firms can also garner higher demands for their products and therefore they can sell them at higher prices.

A firm can alter its reputation based on the product quality it manufactures. However, due to imperfect information in a real market, reputation will not directly reflect the level of product quality the firm currently manufactures. In fact, according to Narasimhan, Ghosh, and Mendez (1993), reputation is a cumulative value that reflects all of the firm's product quality up until present. Accordingly, one can infer that the level of product quality at present is going to affect reputation far into the future. Therefore, a model that can capture the relationship between product quality, reputation, and revenue is needed to fully understand the implications of product development duration and manufacturing ramp-up decisions.

4.3.1 Product Quality – Reputation – Revenue Model

As reviewed in1.1.3.2, while there are a few existing reputation models, there are even fewer that establishes the relationship between product reputation and firm reputation.

The Bass new product diffusion model (1969) assumed that a new product is sold in one of two ways: through an innovator or through an imitator. An innovator purchases the product without knowledge of the product, while an imitator purchases the product after learning about it or seeing it. This can be written as,

$$S(t) = \alpha(M - N) + \beta N(M - N) \tag{4.5}$$

where S is the number of sales of the product, M is the product's market potential (highest saturated amount of products in the market), N is the current number of products in the market. α represents innovator sales (no unit), and β represents imitator sales (unit of 1/number of products). From this equation the innovator sales depend solely on $M - N$, number of customers who have not purchased the product—also called market availability. The imitator sales are based on the market availability and also the number of products already in the market, which Bass uses to represent the popularity of the product.

The NGM Model (Narasimhan, Ghosh et al. 1993) expands on what Bass established. The model keeps the original innovator sales term, but modifies the imitator sales term to take the effect of reputation into account by replacing the number of products in the market to the number of quality-weighted product in the market.

$$S(t) = \alpha(M - N) + \beta N^*(M - N) \tag{4.6}$$

N^* is called quality-weighted number of products in the market, which is defined as

$$N^* = R * D \tag{4.7}$$

where R is the firm reputation and D represents the reputation propagation speed. In this model, reputation is a representation of the product of the sale rate and the quality index of the product in each period that customers expect of the firm, and D is the representation of the durability of firm reputation in unit of time periods. The bigger D is, the longer the firm reputation stays and the harder it is to change. Therefore, $R*D$ represents the amount of products, weighted by their quality, and the duration of the reputation effect in the market.

To change the reputation, the firm has to change the rate of product sale and/or the quality of the products from the previous expected value.

$$\dot{R} = \frac{1}{D}(S * Q_i - R) \tag{4.8}$$

where Q_i is the quality index of the product.

To represent product quality, the concept of quality index—a number that represents comparison between the product failure rate and the base case of what is assumed as 'good' product—is introduced. The quality index is defined as

$$Q_i = e^{\frac{(b_0 - b)}{c}} \tag{4.9}$$

where b_0 and b are the failure rate of what is assumed as a 'good' product and the failure rate of the product being prescribed the index, respectively; c is a constant representing how sensitive the difference between the failure rates is to the quality index.

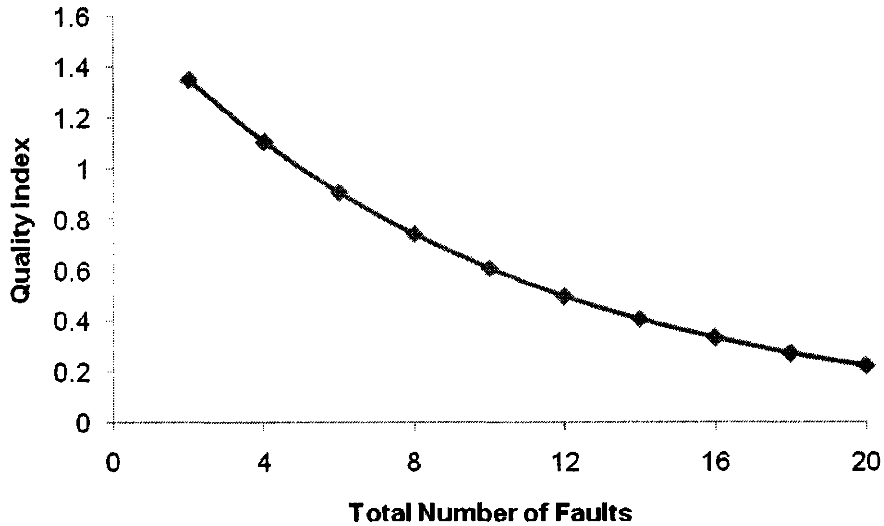

Figure 4-5: Product Quality Index with respect to Total Number of Faults Observed Over 5 Years. Note that base number is 5 faults over 5 years

The reason for an exponential form of quality index instead of a linear one is due to the asymmetric outcome of perceived quality when viewed from failure rates point of view. This is supported by the findings by Donndelinger and Cook (1997), which suggests that customers are willing to pay $300 more for a vehicle with one less repair per year, while the they are willing to pay $700 less for a vehicle with one more repair per year. This suggests that customer sense of quality response more strongly to deterioration than improvement in quality.

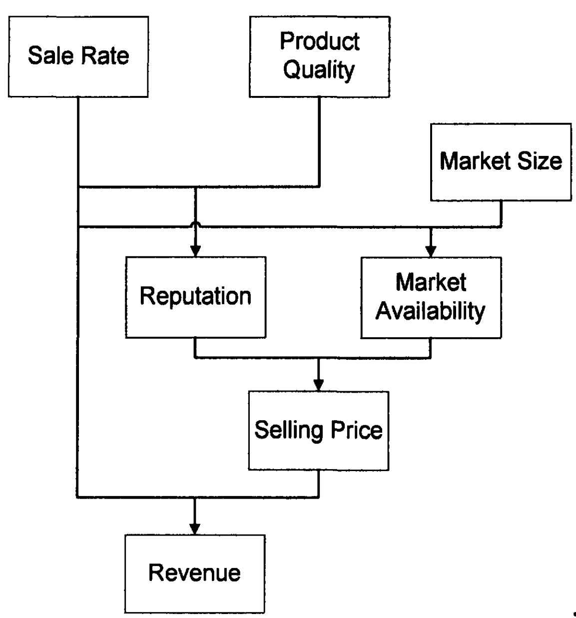

Figure 4-6: Modified NGM Model for Determining Revenue Based on Reputation

In this model, reputation can be interpreted as equal part of product quality and equal part of number of product sale. For example, selling 1000 products with quality index of 0.5 will have the same impact to the firm reputation as selling 500 products with quality index of 1.

The price of the product affects the demand by setting the number of customers who would consider the product. The market potential can be modeled as a function of price as

$$M(P) = \left(\frac{P_0}{P}\right)^e M_0; e > 0 \tag{4.10}$$

where P_0, M_0 are a known demand-price pair of the product and e is the elasticity representing the sensitivity of product demand to the change in price.

In this model, however, it is assumed that all products made can be sold, albeit at different prices based on demand and product quality. Therefore, the reputation model is modified so that the price at which the products are sold for each period reflects the firm's reputation. By combining equations (4.5) - (4.10), the price of a product for each period can be expressed as

$$P = P_0 \left(\frac{M_0}{\frac{S}{\left(\alpha + \beta N^*\right)} + N} \right)^{\frac{1}{e}} \tag{4.11}$$

where now S is the production volume for that period.

The revenue is simply the product of production volume and selling price

$$Rev = P * S. \tag{4.12}$$

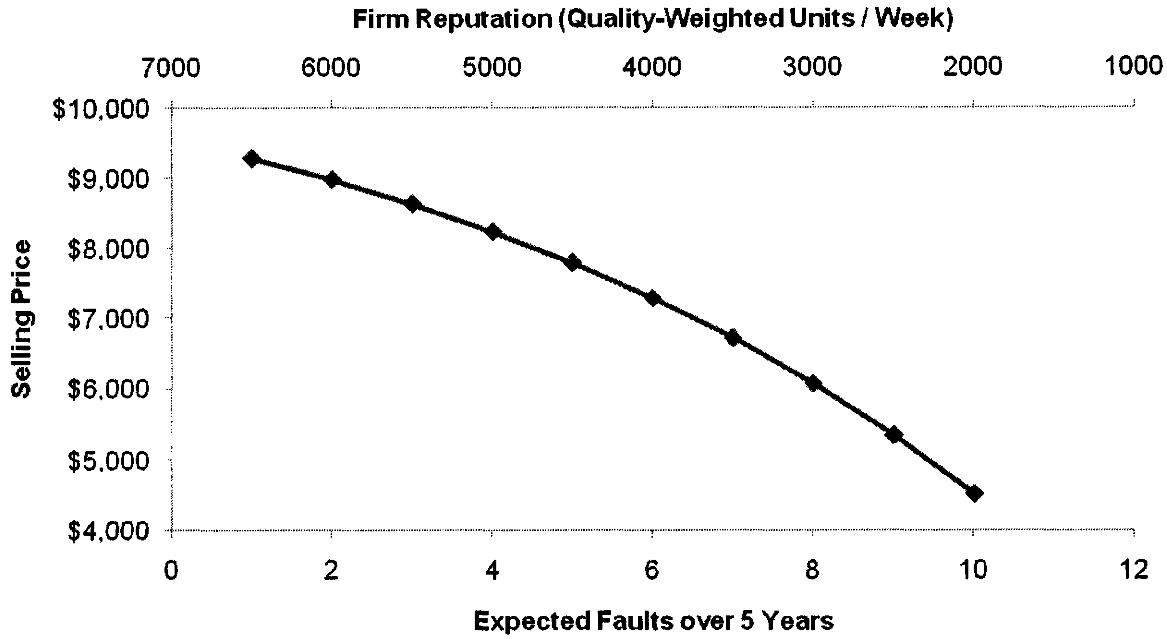

Figure 4-7: Product Selling Price as a Function of Firm Reputation

According to Figure 4-7, firm reputation represents what the customer believes the expected number of faults of the purchased product from the firm will be. For example, if the firm consistently sells products with 2 expected faults in the long run, the firm reputation would be 6000. The higher the firm reputation—the lower the expected faults—the more the customer is willing to pay for the product. The parameters in P_0, M_0, and e in equation (4.11) are varied so that the selling price as a function of reputation fits the measured numbers. (Donndelinger and Cook 1997)

4.3.2 Future Revenue from Improving Product Quality

While the product quality - revenue model reflects the effect of product quality on firm reputation and revenue, the effect only lasts through the product lifecycle. When the product is finally phased out, the revenue flow stops. In reality, however, the firm's change in reputation also affects future revenue flows from future generations of products; customers believe a firm with high reputation will keep manufacturing high quality products, and vice versa. If the model neglects these future cash flows, it may suggest decisions that are shortsighted. The model needs to take future cash flows into account when considering product launch decisions. The effect on future revenue flows can be modeled using modified equations (4.6)-(4.11).

The change in revenue is simply the product of the change in selling price and number of products made over its lifecycle.

$$\Delta Revenue = \Delta P * S \tag{4.13}$$

In each period, the assumption that all products manufactured are sold still stands. The change in the selling price can therefore be expressed as

$$\Delta P = \frac{1}{e} P_0 M_0^{\frac{1}{e}} \left(\frac{S}{\alpha + \beta N^*} + N \right)^{-\frac{1}{e}-1} \left(\frac{S \beta \Delta N^*}{\left(\alpha + \beta N^*\right)^2} \right) \tag{4.14}$$

The change in number of quality-weighted products depends on the change in reputation

$$\Delta N^* = \Delta R * D \tag{4.15}$$

Assuming that the total, non-amortized manufacturing cost for each of the next generations of products is the same as of the current generation, the change in revenue is same as the change in net revenue. However, the change in net revenue from next generations of products are in the future; to take the time value of money effect into account, the change in net revenue must be amortized into present values. Assuming a constant lifecycle of all product generations, the sum of present values of the change in net revenue from the change in reputation due to the current generation of product is

$$NPV(\Delta NetRev) = \frac{\Delta NetRev}{r_{lifecycle}} \tag{4.16}$$

where $r_{lifecycle}$ is the discount rate based on the product lifecycle.

4.4 Conditions for Product Quality Case Comparison

In order to understand the effect of warranty cost and reputation on net revenue and optimal product launch decisions, assumptions regarding comparison between cases must be discussed. To fairly and meaningfully compare different cases of product launch model, with and without reputation consideration, it is important to use the same set of input across the cases.

One difficulty arising from comparison across cases with and without reputation consideration is inconsistent selling price function. While it is simple to use to selling price function for cases with no reputation consideration—the selling price of a product is simply as a linear function with a starting price and decaying rate, the selling price under reputation consideration cannot be set directly. Instead, P_0 in equation (4.11) must be manipulated to achieve the desired price or profit margin. Changing P_0 while keeping other parameters constant sets a new price for which products will be sold under the same reputation throughout the lifecycle. The prices in the periods afterwards are determined by firm reputation and market availability. The model can impose additional fixed decay rate, but that will not be the actual rate of price change. For example, if the firm's reputation is improving, even with an imposed pricing decay, price can still be increasing, albeit at a slower rate than otherwise.

The analysis results show that optimal product launch decisions are dependent on product selling price and, therefore, profit margin. To rule out the effect of profit margin on product launch decisions, case comparison under constant profit margin can be done. This, however, leads to different selling price in each case—since the product cost in each case is different. Furthermore, since product development duration and manufacturing cycle time ramp-up influence the product unit cost, setting price for a profit margin at the base case (product development = 300 days) will still result in the change in profit margin due to the cost change. This leads to a less meaningful way to compare the net revenue across the cases since the selling prices are inconsistent. Although if the focus is to investigate the change in product development duration and cycle time ramp-up, this method is sufficient.

The other approach is to do case comparison under the same selling price function. This leads to the aforementioned effect of inconsistent profit margin on product launch decisions. The benefit of this method is it is a more meaningful method to compare net revenue across the cases, even though it may lead to some cases never able to achieve positive net revenue.

Because the selling price functions with and without reputation consideration cannot be matched, a constant profit margin is proposed as an assumption for comparison across these cases.

4.5 Effect of Product Quality Consideration

Now that the relationship between product quality and warranty cost is established, the impact of considering warranty cost on product launch decisions will be studied.

4.5.1 Effect of Warranty Cost Consideration

The product development and manufacturing ramp-up variables are consistent with section 3.3. The selling price function is starting at \$6500 on the first week with a reduction rate of \$10/week, regardless of product quality, slightly higher than previously. It is assumed that now the manufacturing firm set the price to offset the expected warranty cost and tries to keep 3% profit margin at the base case (product development duration = 300 days). However, there is additional warranty costs associated with the amount of defects that remain in finished products. The failure rate distribution parameters are taken from those in Figure 4-3 and the cost of warranty per fault is \$100.

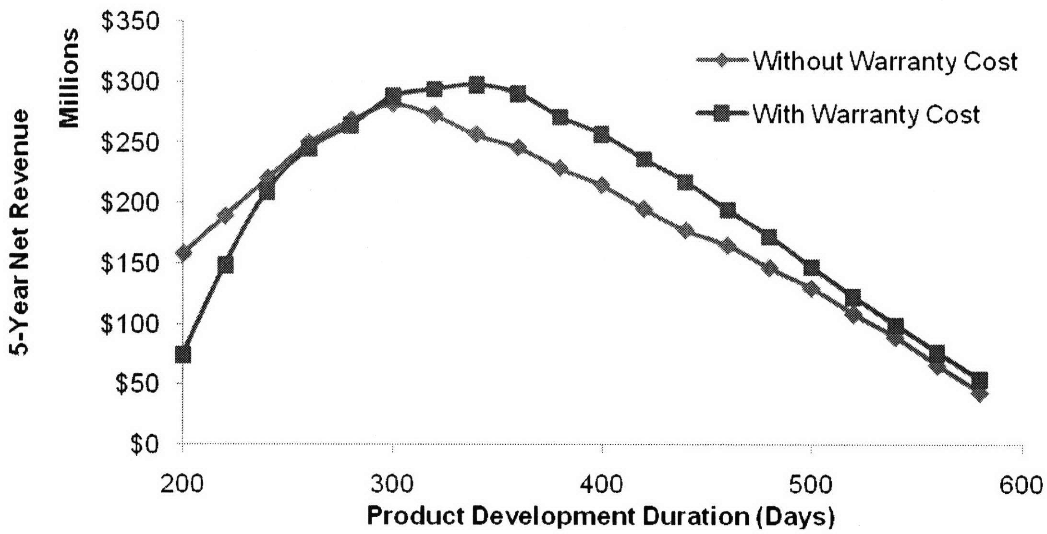

Figure 4-8: 5-Year Net Revenue Comparison with and without Warranty Cost as a Function of Product Development Duration

As expected, Figure 4-8 shows that when considering warranty, the model suggests a longer product development duration. This is to allow product development to eliminate more latent issues before the product goes into manufacturing and let fewer make it through in the finished product as hidden defects. Note that the overall net revenue rises because the selling price is higher than the case without warranty consideration. Figure 4-6 shows the additional cost of warranty as a function of product development duration.

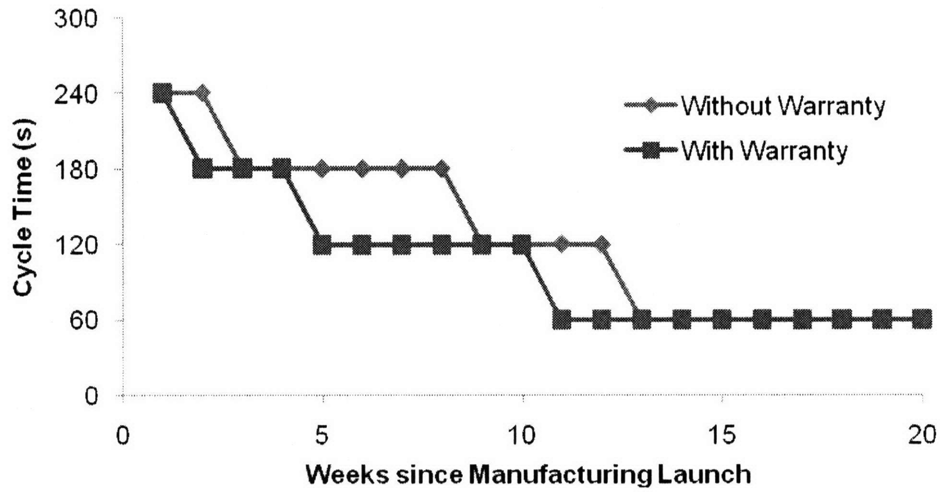

Figure 4-9: Corresponding Optimal Cycle Time Ramp-up Strategy for Optimal Product Development Duration with and without Warranty Cost

Due to the lengthened product development duration suggested by the model, the cycle time ramp-up when considering warranty is faster because the product development process eliminates most of the issues before the start of manufacturing. This allows for the production speed to be increased more rapidly without suffering excessive manufacturing events.

4.5.2 Effect of Reputation Consideration

The same set of inputs used all previous cases is again used; the only difference is that now the selling price is a function of reputation as opposed to a function of time. According to equation (4.11), known market potential, price, and elasticity are $M_0 = 4000000$, $P_0 = 6369$, and $e = 1.3$, respectively. The elasticity is taken from economics literature on the price elasticity for demand of durable goods. For the sales term, innovator sales coefficient $\alpha = 3*10^{-4}$ and imitator sales coefficient $\beta = 7.3*10^{-6}$and reputation delay $D = 1000$. (Narasimhan, Ghosh et al. 1993)

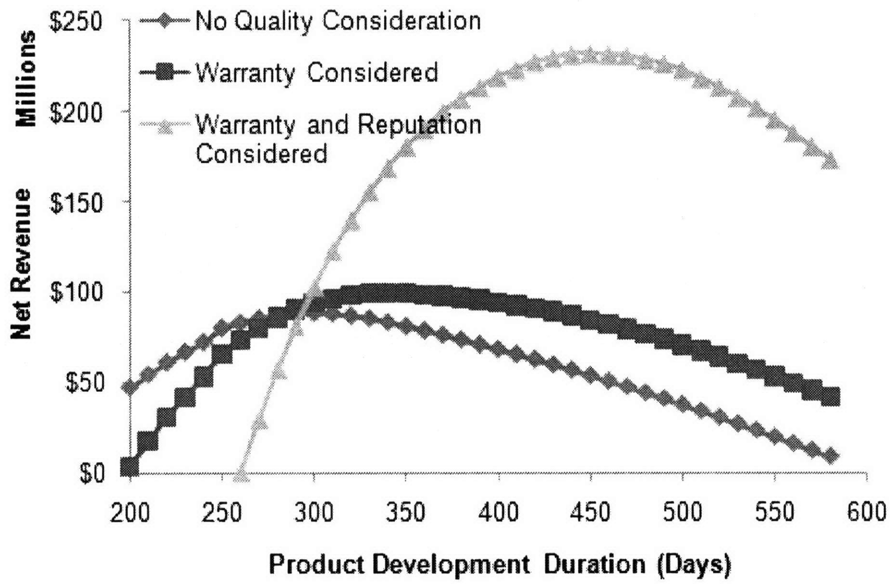

Figure 4-10: Net Revenue vs Product Development Duration Comparison between all three cases

With the additional consideration of the effect of product quality on firm reputation and revenue, the model now suggests extending the product development duration substantially to 450 days from 300 days with no quality consideration and 340 days with warranty considerations only. This is because now there is an additional downside to producing low quality products. Low quality products build bad reputation causing the firm to reduce the price in order to be able to sell its inventory. Additionally, bad reputation accumulated from this generation of product also affects any subsequent product generations. The firm also has to sell them at lower prices than if than if it has a good reputation. Figure 4-11 illustrates effect of reputation on the net revenue of product launch.

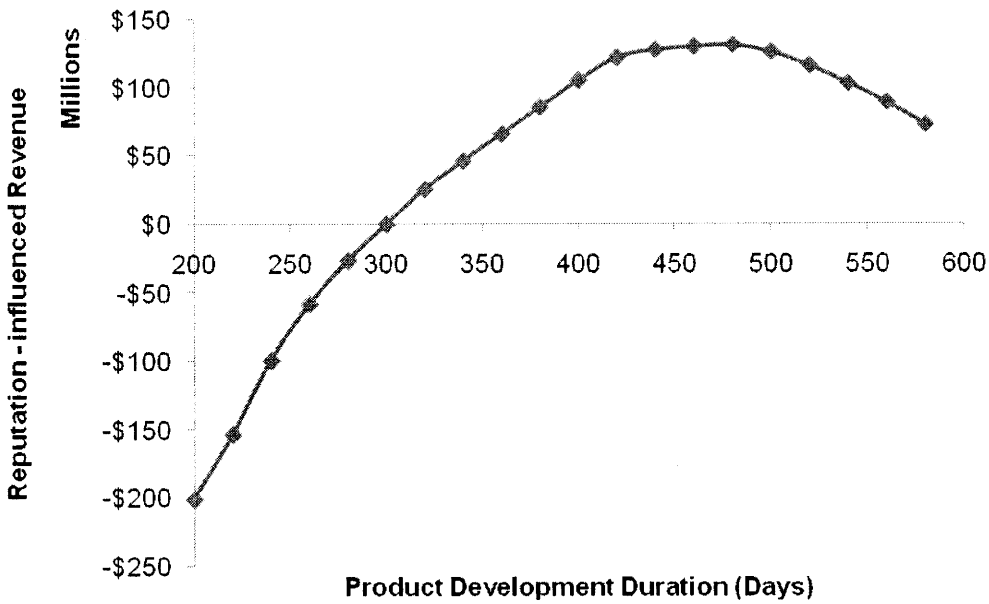

Figure 4-11: Reputation-Influenced Revenue over Product Lifecycle with respect to Product Development Duration

Figure 4-11 shows that when considering reputation, there is a negative impact on revenue when product development is shorter than 300 days (the base case). This is because the quality of a product released after short product development duration is low and creates a negative reputation for the firm. With low reputation, the firm will have to cut prices substantially to be able to sell the products (See Figure 4-7). For product development durations longer than 300 days, there is a positive impact on revenue since better quality products generate good reputation for the firm. However, there is also a negative impact on revenue for overly extending product development duration: the effect of time value of revenue. The later the products are manufactured and sold, even at the same selling price, the value of revenue generated is less than earlier products.

The maximum net revenue when considering only warranty is at 340 days and the maximum reputation-influenced revenue is at 480 days; these two results combine to generate optimal net revenue at 450 days when considering warranty and reputation.

The cycle time ramp-up for the case which takes into account both warranty and reputation is the fastest one: starting at 180 seconds, speeding up to 120 seconds by week 3, and reaching full speed by week 7. Again, this is due to the additional time in product development that the model suggested, eliminating even more latent issues before manufacturing launch, allowing faster ramp-up.

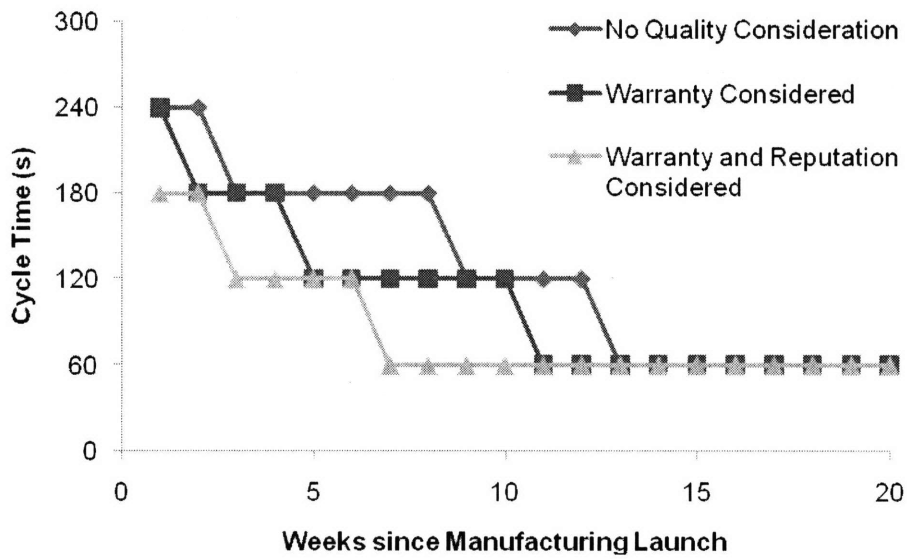

Figure 4-12: Cycle Time Ramp-up Strategy Comparison between Scenarios

An exploration of the effect of quality considerations on optimal product launch decisions shows that longer product development durations are optimal. This is the case when considering both warranty costs and the impact on firm reputation with the changes from reputation have the greater impact.

5 Factors Influencing Product Launch Decisions

The method to model the effects of product launch decisions on the cash flows of current and future generations of products has been established. Thus far, the model inputs are set to a realistic base case to facilitate the understanding of interactions between the cash flows. However, the merit of creating the product launch model is not only to predict the optimal product decisions for a specific situation but to use it to explore how the changes in any of its input affect the decisions and to identify the underlying drivers of the changes in the decisions. Thus the model will now be used to explore the effect of changes in firm strategies, selling price, price decay rates, warranty rates, and reputation on product launch decisions.

Factors than can affect product launch decisions are divided into two categories: endogenous and exogenous factors. Since the model is intended to help managers make effective product launch decisions, the criteria for factor categorization are based on their relationship with the physical processes involved in product launch. Endogenous factors are directly related to the processes of the development and manufacturing of the products themselves. Exogenous factors are not related to the processes. For example, a firm's manufacturing learning is an endogenous factor, directly involved in the rate at which the manufacturing team eliminates latent issues. On the other hand, profit margin is an exogenous factor, even though it is the manufacturing firm that nominally decides the price, and profit margin, at which the product would be sold. This is because the pricing decision is in reality dictated by the market and competitors and is not directly related to the product development and product manufacturing.

Section 4.4 discusses the strengths and weaknesses of using constant profit margin versus constant selling price function in case comparisons. Constant profit margin, while less meaningful when the focus is on the change in product launch decisions, has the flexibility of providing common ground for cases with and without reputation consideration. However, in this Chapter, reputation considerations will be included in all analyses. Therefore, the analyses will employ a single selling function which is set so that profit margin at the base case (product development duration = 300 days) is 3%, where $P_0 = 6396$.

5.1 Endogenous Factors

Endogenous factors are often related to the product development and manufacturing processes. These are factors that represent the efficiency of the firm at designing or manufacturing. Firm strategies on these processes can significantly affect these factors, resulting in changes in the product launch performance. Therefore, a manager will have to make adjustments in product launch decisions accordingly.

5.1.1 Change in Product Development Initial Latent Issues

A firm may be especially efficient in introducing new products by intentionally designing them with product architectures, subsystems, and major components reused from or as slightly varied versions of older generations. Indeed, subsystem architecture re-use even without component re-use can greatly help in avoiding (and eliminating) defects in design. Firms may also achieve particularly efficient product development cycles by focusing on either additional features or improvement of the product on a few parts, leaving other possible improvements to be worked on in the next generation. While this strategy limits the scope of product improvements from the previous generation of products, it helps facilitate the product development team to focus their efforts. The team will be able to deal with fewer and better understood problems, because most of the problems have already been eliminated or at least encountered in products from the previous generation.

To represent this type of effect in the model, the DSM rework probability matrix is modified to reflect the reduced (or increased) level of activities in product development. Each probability entry is increased or decreased by the same percentage. This results in a change in the total number of rework events and the total number of latent issues. The number of latent issues can be plotted as a function of product development duration and the manufacturing and customer reaction models can then be employed to calculate the net revenue over the product lifecycle. The optimal product development duration for each case is illustrated in

Figure 5-1.

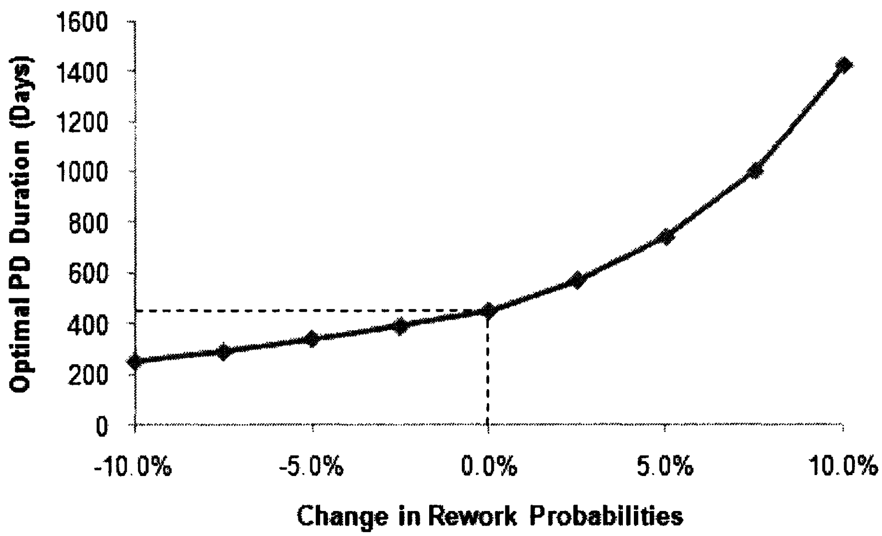

Figure 5-1: Optimal Product Development Duration with varying Product Development Rework Probability Change. Note that negative percentage is an improvement, and vice versa.

As expected, improvements in product development process (i.e., decrease in rework probability) result in significantly reduced optimal durations. At the base case (0% change), the optimal product development duration is 450 days. By reducing the rework probabilities by 10%, the optimal duration drops to 240 days. On the other hand, by increasing the probabilities by 10%, the optimal duration increases exponentially to 1470 days. This asymmetry is the result of the solution being bound one-sided by its lower limit: the smallest possible product development duration is 120 days—the average sum of all activity durations. Increasing rework probabilities further causes the DSM model run time to increase exponentially (indeed above 12% rework the failure rate becomes so high that PD is not completed) and thus the maximum increase is kept at 10%.

The DSM shows that lowering the rework probabilities between activities leads to fewer initial latent issues. Fewer latent issues allow the product development team to put the product design into manufacturing sooner. This reduces the product development cost and helps the firm sell products earlier.

It is important to note the trend of latent issues at the optimal product development duration, the number of latent issues are 620, 800, 1200, 1500, and 1900 issues per thousand products at -10%, -5%, 0%, 5%, and 10% changes, respectively. Note that the rate of decrease of latent issues is smaller with longer product development duration. At the optimal duration, the loss of revenue from longer duration outweighs the increase in revenue from improved product quality and decrease in manufacturing cost from fewer latent issues. With smaller initial latent issues from improved rework probabilities, the rate of decrease of latent issues gets to the critical rate at a smaller number of latent issues, leading to the optimal duration where the number of latent issues is smaller.

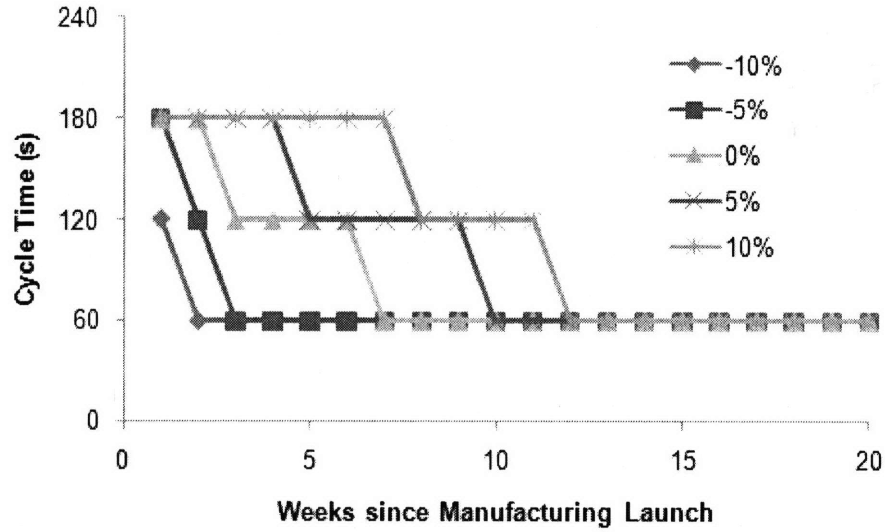

Figure 5-2: Optimal Cycle Time Ramp-up under various Rework Probability Improvements

Figure 5-2 shows that the improvement in rework probabilities also leads to faster cycle time ramp-up. At the base case (0%), the optimal cycle time at product development = 450 days is to start manufacturing with 180 s cycle time for two weeks, 120 s for 4 weeks, and then proceed to manufacture at full speed. At -10% change (10% improvement), the optimal cycle time is to manufacture at 120 s cycle time and ramp up to full speed in the second week. On the other hand, at 10% change (10% increase in probabilities), the optimal cycle time is to start manufacture at 180 s cycle time for 7 weeks, 120 s for 4 weeks, and then to full speed at week 12.

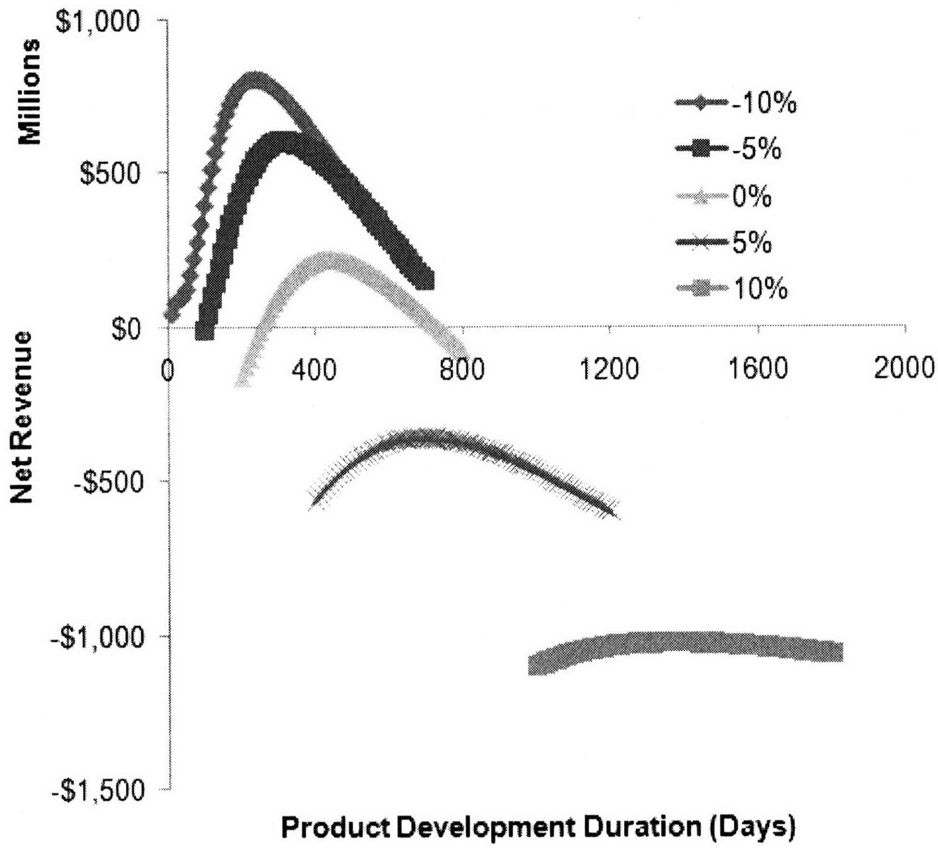

Figure 5-3: Net Revenues with respect to Product Development Duration Decisions under changes in Rework Probabilities

Figure 5-3 shows the comparison of net revenues under varying changes in rework probabilities when keeping pricing function consistent. As expected, lower rework probabilities lead to smaller initial latent issues, shorter product development duration, smaller product development cost, and, therefore, higher net revenue. At -10% change, the optimal net revenue is at $800 million, while at 10% change, the optimal net revenue is at $-1 billion. It should also be noted that fairly small deterioration of the PD capability can make it impossible for the firm to make a profit at any PD timing strategy.

5.1.2 Change in Firm's Manufacturing Learning

During manufacturing, there are remaining latent issues that have not all been eliminated in product development. These latent issues can be resolved during manufacturing through learning. After a manufacturing event caused by one of the issues occurs, a worker will investigate it. This may lead to the manufacturing workers discovering the root cause of the event. Once the design is modified to resolve that root cause, the issues will be eliminated from all subsequent products in manufacturing. In the model, this process is represented by a probability: the number of issues eliminated during a period of manufacturing is the product of this probability and number of manufacturing events. For firms which are particularly skilled at resolving issues in manufacturing, this probability should be lower. Changes in this probability will affect the issue elimination during manufacturing, which will affect the optimal product development duration. The product quality will also be affected because issues are eliminated at a different rate during the manufacturing period, changing the amount of hidden defects in finished products.

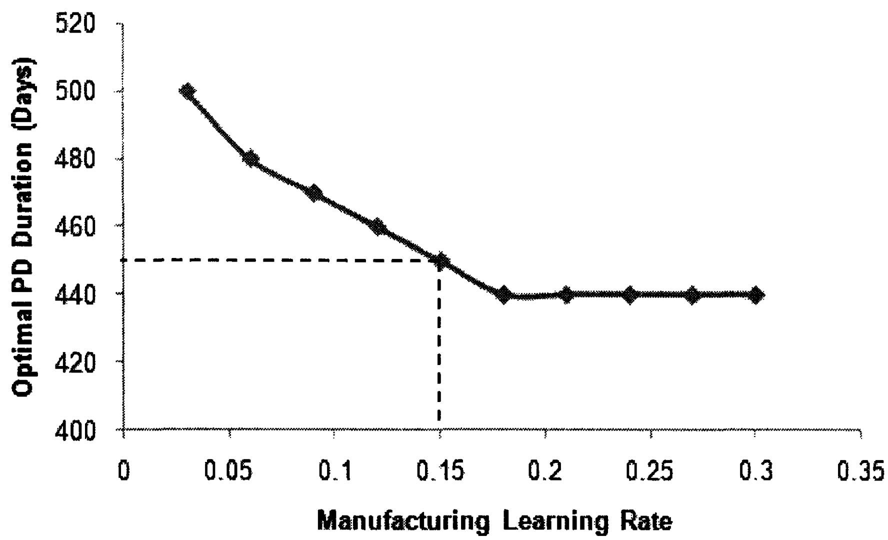

Figure 5-4: Optimal Product Development Duration with respect to Varying Latent Issue Elimination Probability. Dash line represents the base case when probability = 0.15.

According to Figure 5-4, the higher the probability of solving latent issues from manufacturing events, the shorter the model suggests the optimal product development duration need be. Higher manufacturing learning probabilities lead to higher rates of issue elimination, allowing managers to shorten the product development duration because the increase in latent issues that might be expected from shorten product development cycles is offset by the increase in the elimination rate of issue during manufacturing. High elimination rates will also improve product quality since more issues will be resolved earlier in manufacturing, which will also drive the firm to shorten the product development duration in order to be able to sell the products earlier.

The base case is where the probability = 0.15 (dash line). By lowering this probability and slowing the learning rate, the optimal product development duration increases linearly until probability = 0.03 below which the duration increases more significantly. This is because at extremely slow latent issue elimination rates, the manufacturing workers are barely able to resolve latent issues in the product design, causing manufacturing and warranty cost increase and reputation decrease.

On the other hand, firms with improved issue elimination rates, i.e. those with probabilities above 0.3, cannot expect additional reductions below 400 days in their optimal product development duration. This is because regardless of the issues elimination rate, shortening the product development duration will lead to high numbers of latent issues in the products manufactured early in manufacturing ramp-up and, thus, low quality. This will affect the firm reputation early in the product lifecycle, preventing the products from selling at a price as high as they can potentially command.

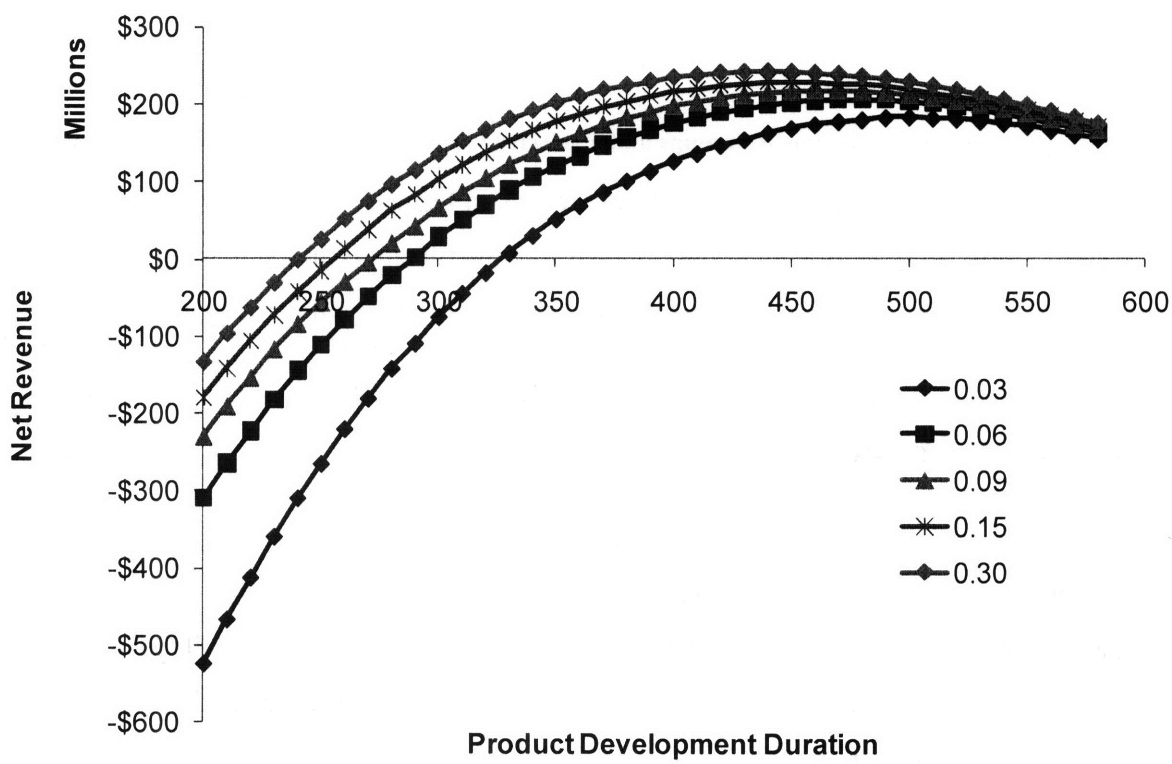

Figure 5-5: Net Revenue with respect to Product Development Duration under selected Manufacturing Learning Rates

Figure 5-5 shows the net revenue is increasing with higher manufacturing learning rates. The improvement is more significant at shorter product development duration since faster learning rate is more important when there are more latent issues. The base case (manufacturing learning rate = 0.15) optimal net revenue is $210 million. At learning rate = 0.3, the net revenue is improved by approximately 5%, while at learning rate = 0.3, the net revenue decreased by 10%. It is also important to note that difference in net revenue is greater at shorter product development duration. This is because the change in manufacturing learning rate has a more significant impact when there are more latent issues.

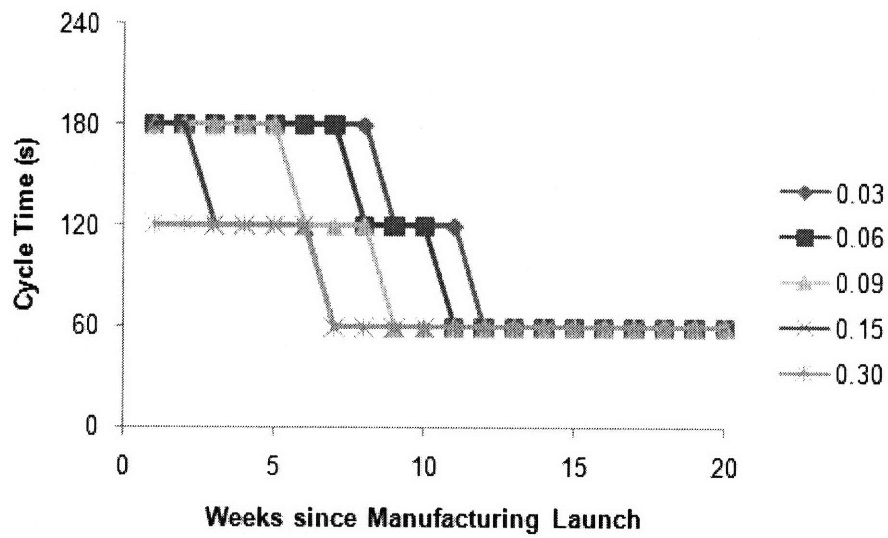

Figure 5-6: Optimal Cycle Time Ramp-ups under selected various Manufacturing Learning Rates

Figure 5-6 shows that the higher the learning rate results in faster cycle time ramp-up. Even though shorter product development duration leads to higher latent issues at manufacturing launch and increase the manufacturing events, but the increase in manufacturing rate also allows the manufacturing workers to eliminate more issues, thus speeding the cycle time ramp-up.

5.2 Exogenous Factors

Factors unrelated to the manufacturing of the products are categorized as exogenous factors. These factors may not be readily apparent to the managers at the time of product manufacturing or are simply unpredictable, yet they may have strong influences on the profitability of product launch. These factors include decaying prices, changing profit margins, hidden defect failure rates, and the initial product reputation.

5.2.1 Decaying Prices

In a tightly competitive market, especially for high technology products, customers are always looking out for 'the newest best thing.' Multiple firms release one product after another, competing to be the newest product on the market. This limits the window of opportunity for a firm to launch and capitalize on any one product. In this scenario, it is assumed that the firm will have to aggressively cut selling prices to incentivize customer demand after product launch. The effect of the rate of decaying price on product launch profitability is investigated in Figure 5-7.

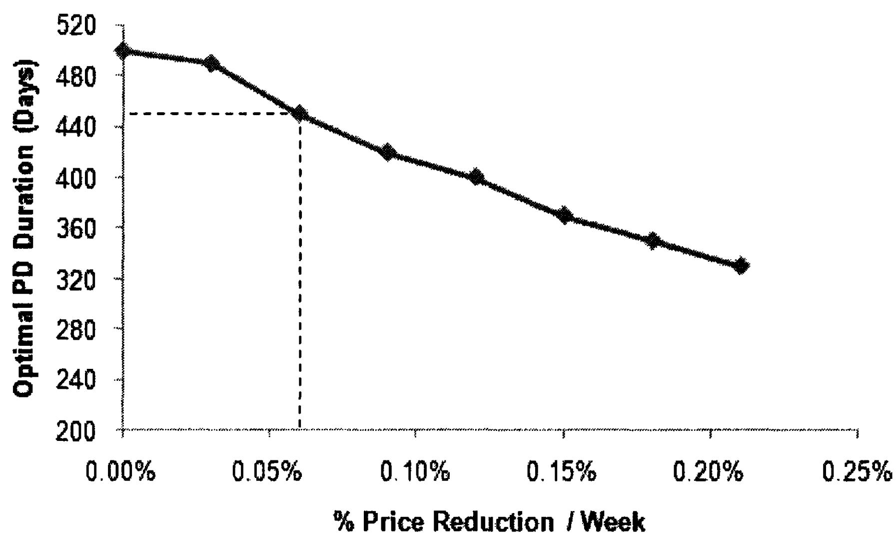

Figure 5-7: Optimal Product Development Duration under Various Price Reduction Rate

Note that the units on the x-axis are the percent price reduction per week. The percentage of price reduction is based on the starting selling price, which is constant through all cases. Although the percentage seems small, it is a constant weekly rate. For example a 0.03% price reduction per week translates to a 1.5% price reduction per year and a 7.5% price reduction over the 5-year life cycle. The base case is a 0.06% price reduction rate, leading to optimal product development duration at 450 days.

As expected, the faster the rate of price reduction, the shorter the model suggests product development should be. This is so that the firm can make as much revenue from manufacturing products as early as possible and sell them while the price is still high. Even though the firm would still need to be concerned about product quality, the more aggressive the price cut, the less important of a factor product quality becomes to the performance of product launch.

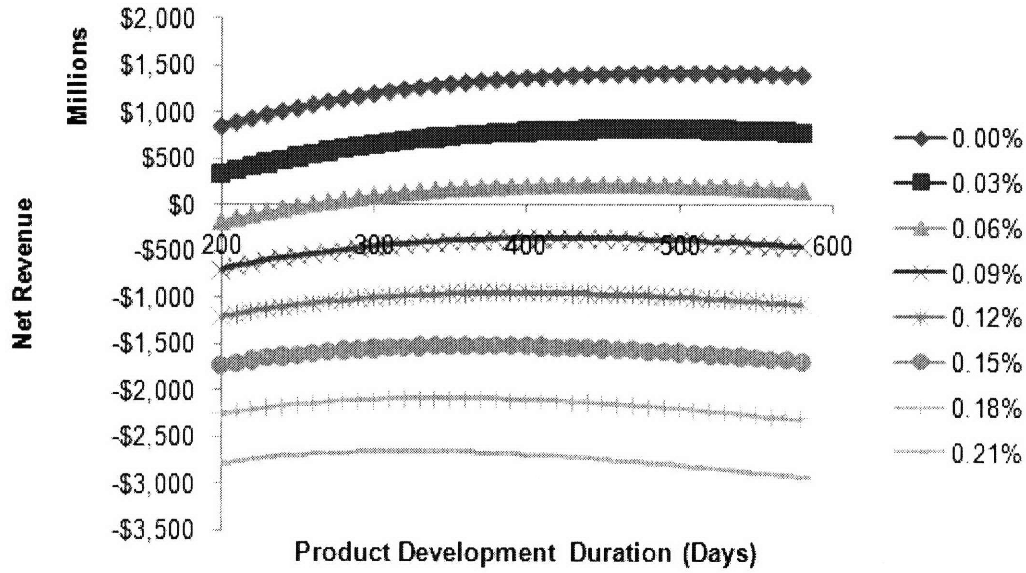

Figure 5-8: Net Revenue with respect to Product Development Duration under various Price Decay Rates

As Figure 5-8, faster price decay results in lower net revenue over the product lifecycle. Also note that difference in net revenue between cases is larger the longer product development duration is. This is because the longer product development duration is, the larger the different in selling prices becomes due to constant price reductions.

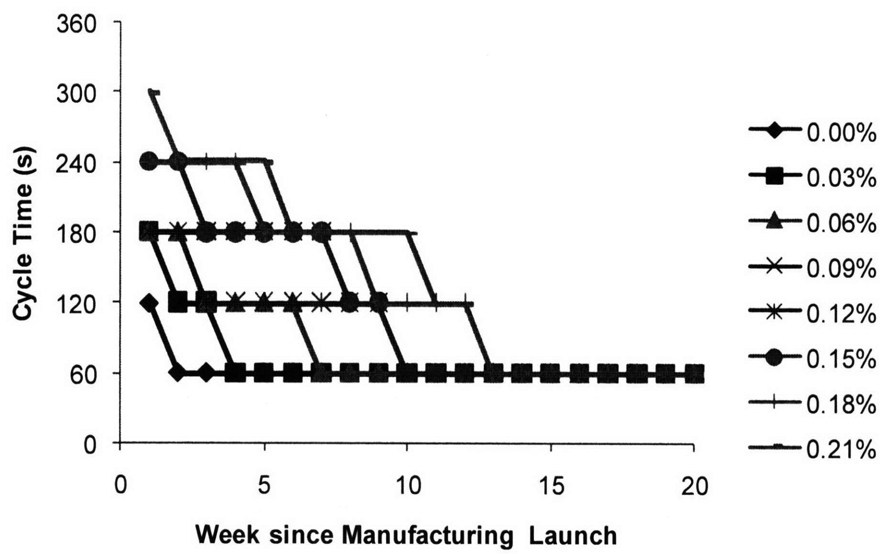

Figure 5-9: Optimal Cycle Time Ramp-up under various Price Decay Rates

Since faster price decay leads to shorter product development duration, which in turns lead to higher latent issues, the model suggests that manufacturing cycle time ramp-up should be slower to avoid high cost from manufacturing events. For example, at 0.21% / week price reduction, the optimal product development duration is at 330 days, leading to cycle time starting out at 300 s, and reaching full speed only at week 13. While at no price reduction, the optimal duration is at 500 days, and the cycle time starts out at 120 s and reaching full speed by the second week.

5.2.2 Profit Margin

In manufacturing industries, the product profit margin can vary widely depending on the type of product, demand, and many other factors. In general, profit margin is defined by the total profit divided by the total revenue. However, for the purpose of this study, it is defined as net revenue divided by the total revenue since the focus of the study is on firm's manufacturing decisions; managers do not yet know the profit the product will make, therefore a representative price is set to facilitate net revenue calculation.

Note that profit margin is not a direct input to the model; in order to achieve a specified profit margin, the price – reputation equation parameter P_0 (equation (4.11)) is instead set with the base case of product development duration = 300 days.

Here, optimal product development duration is calculated with respect to various starting selling prices over the 5-year life cycle of the product.

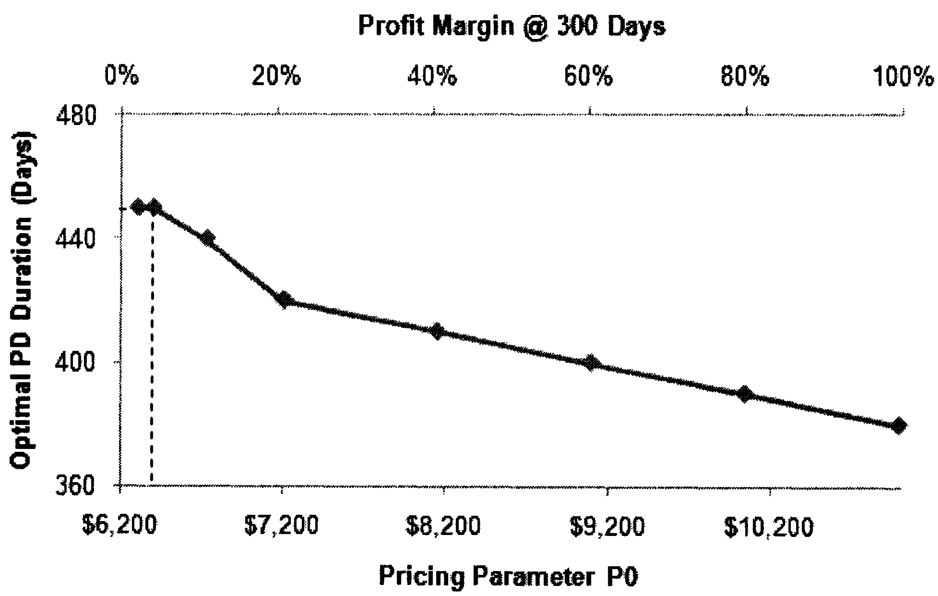

Figure 5-10: Optimal Product Development Duration for various Starting Prices.

Note that the profit margin percentage is for the selling price at base case at 300 days. Once the selling price for the base case is found, it is fixed and the model tests other product development duration for better outcomes.

At the base case, using $P_0 = 6396$ corresponding to a 3% profit margin, the optimal product development duration is 450 days. The model suggests that longer product development durations are optimal when the product profit margin is lower. This is to avoid high manufacturing costs and low product quality from latent issues. This suggests that when the profit per vehicle is low, the way to increase net revenue is to reduce cost and improve reputation. When the profit margin is low, increasing the product development duration means there is less time to manufacture products before they become obsolete, but the revenue loss from them is small compared to the cost saving and increase in revenue from improved quality.

On the other hand, when the profit margin is high, the model suggests short product development durations. This will increase the cost and keep reputation from reaching the highest possible levels. This suggests that for high profit margin, firms should seek to make more products and make them early. When the profit margin is high, the increase in revenue from more products made during lengthened manufacturing period because of shortened product development duration is higher than the cost saving and revenue increase from improved quality.

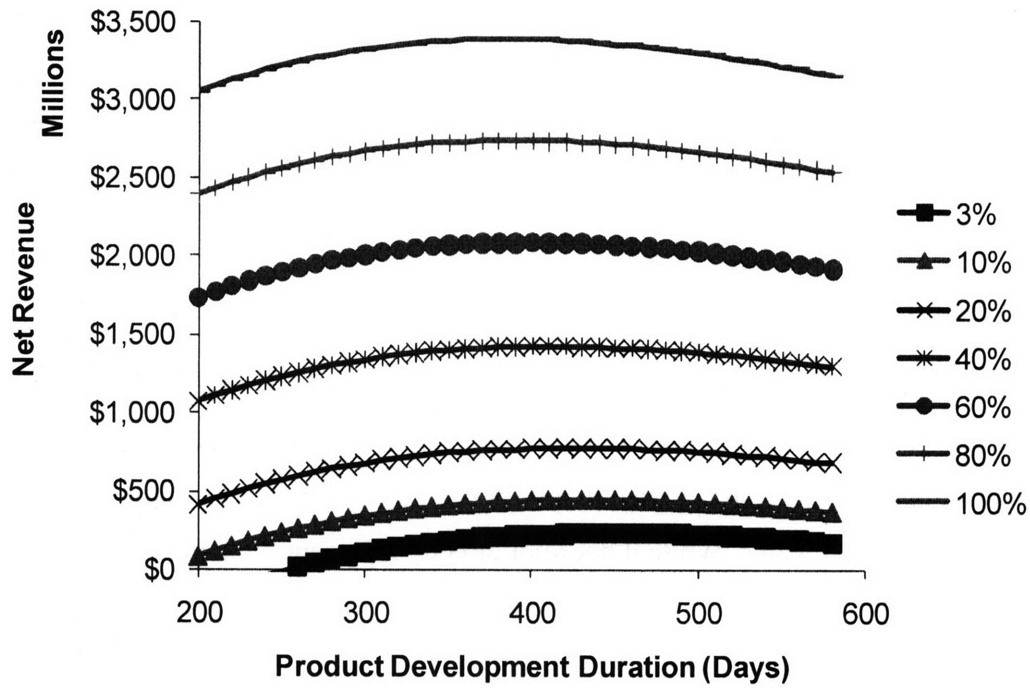

Figure 5-11: Net Revenue with respect to Product Development Duration under various Profit Margins

As Figure 5-11 shows, the higher P_0—corresponding to higher profit margin—leads to higher net revenue. At P_0 = $11000, corresponding to 100% profit margin, the optimal net revenue is $3.3 billion, while at P_0 = 6396, corresponding to 3% profit margin, the optimal net revenue is $200 million.

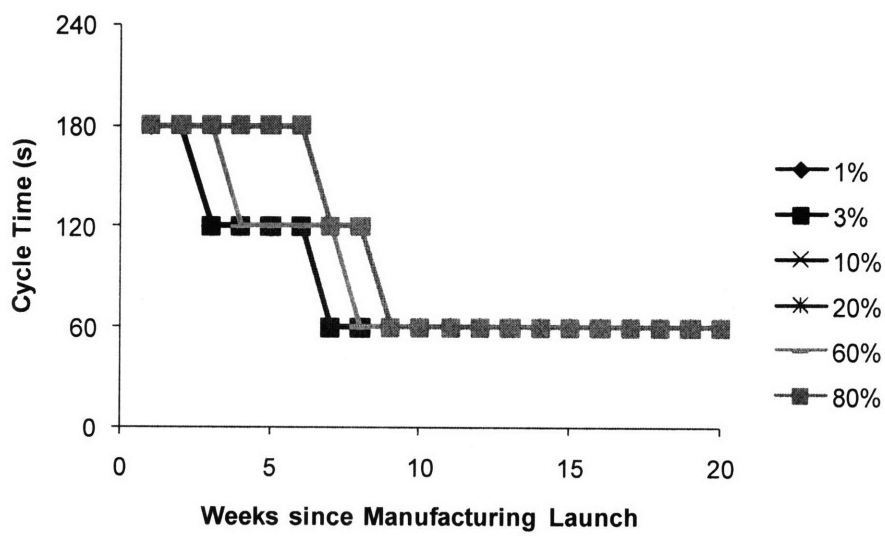

Figure 5-12: Optimal Cycle Time Ramp-ups under various Profit Margins

Figure 5-12 shows that a higher profit margin leads to shorter product development duration and higher latent issues, resulting in the model suggesting slower cycle time ramp-up to avoid high manufacturing cost. At 80% profit margin, the model suggests that cycle time for the first week is 180 s and stays constant for 6 weeks, speeding up to 120 s for two weeks, and finally reaching full speed at week 9. At 3% profit margin, the cycle time should also start at 180 s, but should stay constant for only 2 weeks, then speed up to 120 s for 4 weeks before reaching full speed at week 7.

5.2.3 Hidden Defect Failure Rate

While firms may be able to control the number of hidden defects making it into the finished products through inspection, they have no control over the failure rate of the hidden defects. λ parameter in the Weibull distribution is varied to investigate how the change in failure rate affects the product launch decisions. While it does not directly represent the failure rate of a product, equation (4.3) shows that as λ increases, the failure rate of a hidden defect decreases.

Again, note that the failure rate is not a direct input. Therefore, to explore a range of failure rates, the Weibull parameter λ is varied instead. To eliminate the effect of differences in profit margin, the analysis is done in using constant profit at 3% at 300 days for each failure rate case.

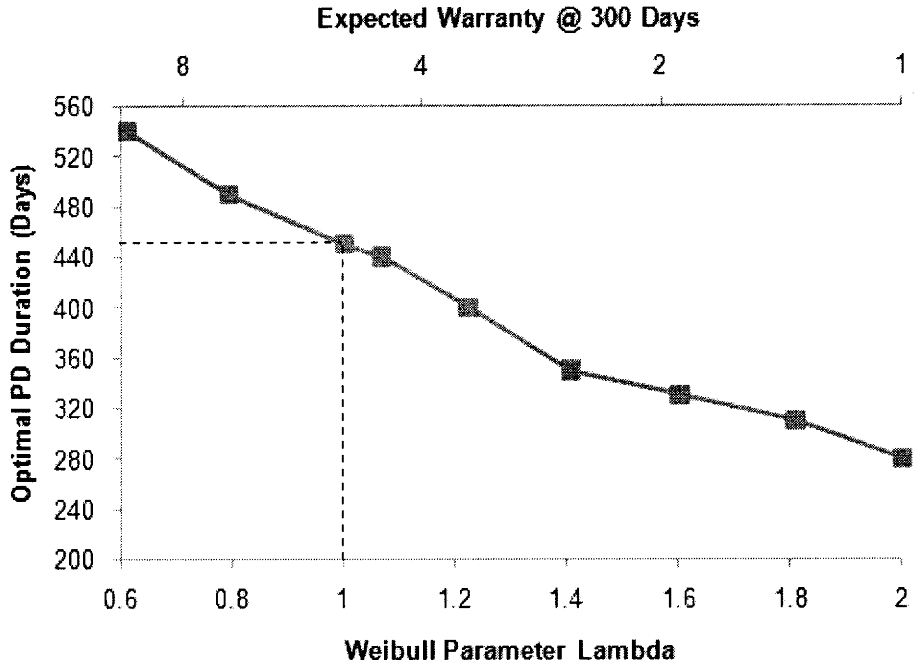

Figure 5-13: Optimal Product Development Duration with Various Failure Rates by changing λ

At the base case, when $\lambda = 1$ (corresponding to 5 faults over 5 years @ product development duration = 300 days), the optimal product development duration is 450 days. Lower λs lead to higher failure rates and therefore higher expected warranty claims. This means that with the same number of hidden defects in the finished products, the customer will encounter more faults. The corresponding expected number of errors for each λ is shown on the secondary horizontal axis. The values of lambda at the two ends, 0.6 and 2, corresponds to the expected number of errors of 10 and 1 over 5 years, respectively, while the typical range of number of faults for automotive industry is from 2 to 8 over 5 years. (Arnum 2006)

This not only leads to the firm paying more for the warranty cost, but also has a greater impact on firm reputation because of the lower product quality. Note that while λ decreases in a linear scale, the failure rate and expected warranty claims increase exponentially. The effect is particularly strong because the failure rate not only drives the warranty cost, but also the quality index, reputation, and revenue.

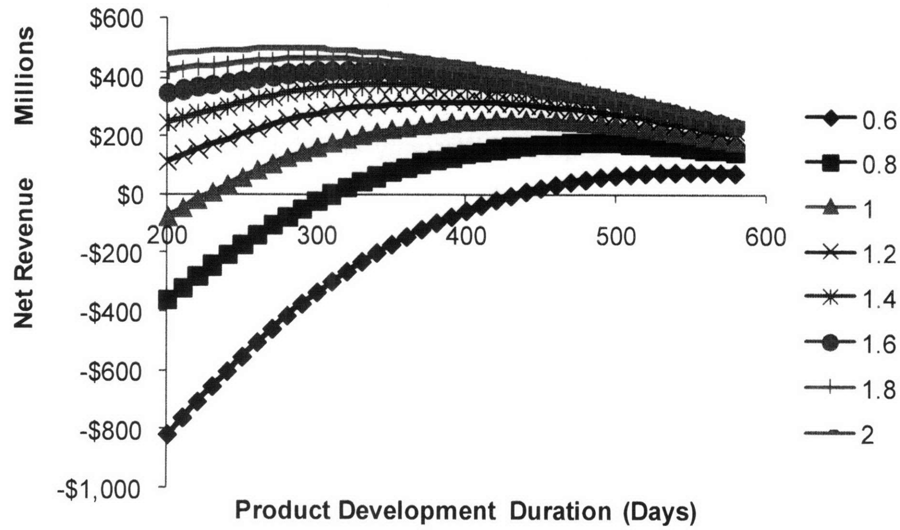

Figure 5-14: Net Revenue with respect to Product Development Duration under various Weibull Parameter λ's

As Figure 5-14 suggests, a higher hidden issue failure rate (smaller λ) leads to smaller lifecycle net revenue due to the increasing warranty cost and lower revenue from lower reputation. This effect is especially significant in shorter product development durations due to higher latent issues at manufacturing launch and, therefore, higher hidden defects in finished products.

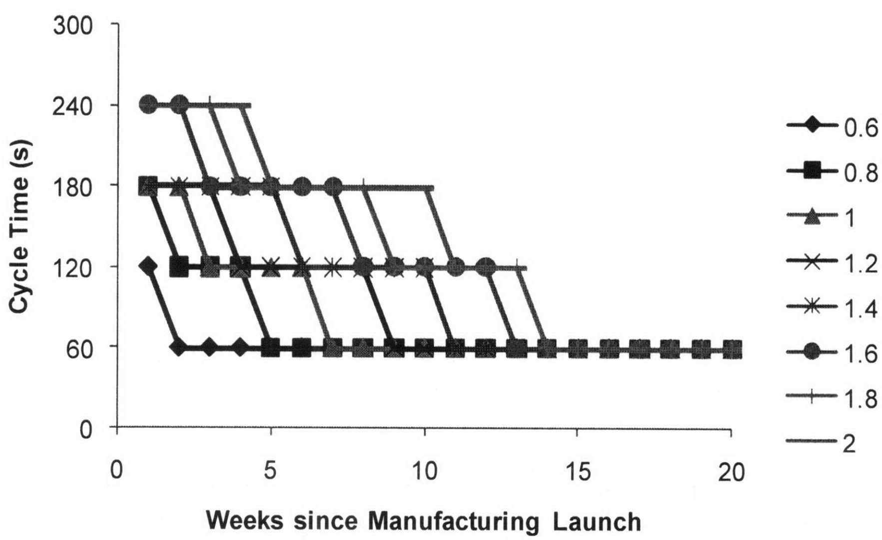

Figure 5-15: Optimal Cycle Time Ramp-up under various Weibull Parameter λ's

Figure 5-15 suggests that for the higher hidden issue failure rate (smaller λ) is, which leads to a longer product development duration, the slower the cycle time ramp-up should be to avoid the high manufacturing cost from high latent issues. For $\lambda = 2$, the optimal ramp-up starts at 240 s for

4 weeks, 180 s for 6 weeks, 120 s for 3 weeks before reaching full speed at week 14. On the other end, for $\lambda = 0.6$, the optimal ramp-up starts at 120 s and reaches full speed by the second week.

5.2.4 Initial Reputation

The firm reputation represents the expected level of quality and amount of products the firm will sell. This leads to the customers believing that the firm will release high quality products and therefore high demands for the firm.

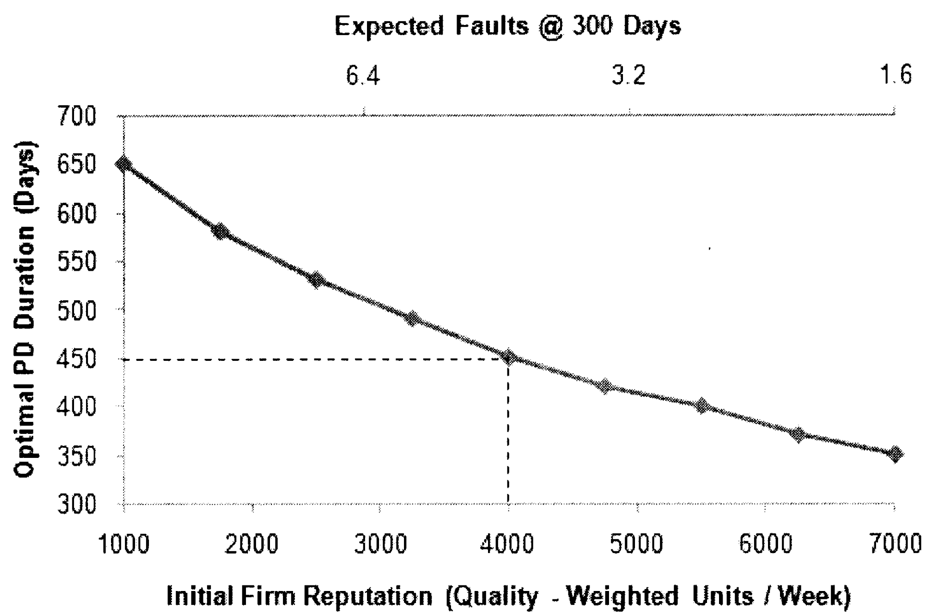

Figure 5-16: Optimal Product Development Duration with Various Initial Firm Reputations

Initial reputation of the firm affects the optimal product development duration. The higher the reputation of the firm, the shorter the model suggests product development duration need be. Since high reputation raises the customer demand and allows the firm to raise the selling price, the firm should shorten product development duration to manufacture the products and start selling as early as possible. With high reputation, there is a 'hype' effect for the products where customer demand builds up very quickly in expectation of the release date and the firm can sell the products at a high price. The firm can then take advantage of this demand by releasing the products to the market as soon as it can. Of course, if they continue to the point of low quality, their reputation will eventually fall and thus this strategy must be monitored carefully.

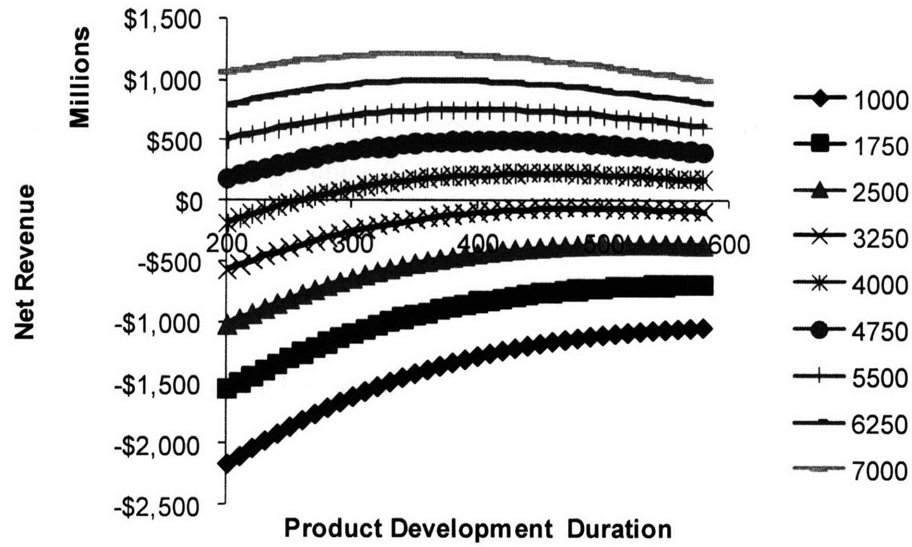

Figure 5-17: Net Revenue with respect to Product Development Duration under various Initial Firm Reputations

As Figure 5-17 suggests, the lifecycle net revenue is higher when the firm has higher initial reputation. This is because, with high reputation, the firm can sell the product at a higher price. For reputation = 1000, the optimal net revenue is -$1 billion. On the other hand, for reputation = 7000, the optimal net revenue is at $1.2 billion. The effect is especially strong at shorter product development duration because of more hidden defects.

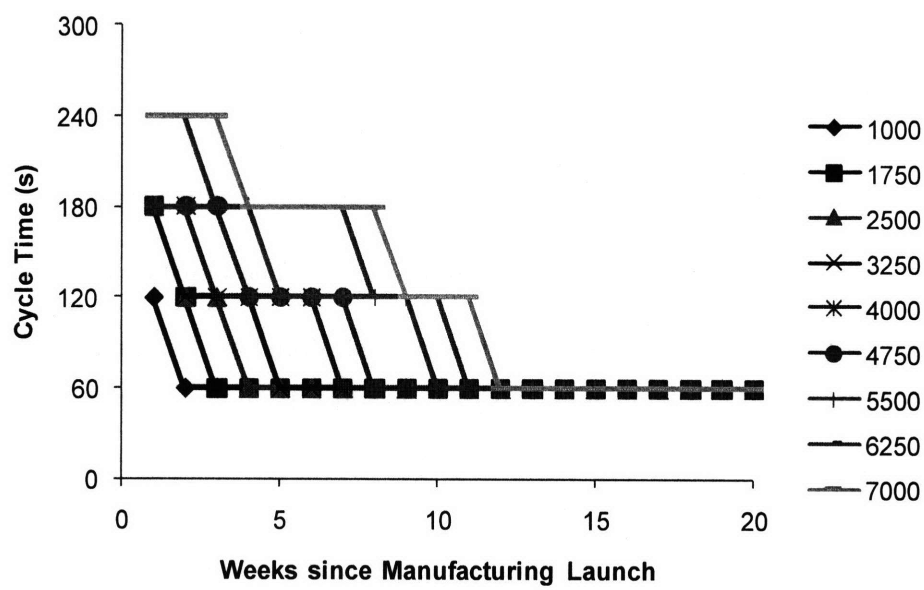

Figure 5-18: Optimal Cycle Time Ramp-ups under various Initial Reputations

As Figure 5-18 shows, the higher initial reputation of the firm is, leading to shorter product development duration, the slower the optimal cycle time ramp-up is. Again, this is to avoid the high manufacturing cost from more latent issues. For reputation = 1000, the optimal ramp-up starts at 120 s and reaches full speed by the second week, while for reputation = 7000, the ramp-up starts at 240 s for 3 weeks, 180 s for 5 weeks, 120 s for 3 weeks, and reaches full speed at week 12.

5.3 Insights from Case Studies

5.3.1 Endogenous vs Exogenous Factor Effects on Product Launch Decisions

One of the most important findings from the case studies is the difference between the effect of endogenous and exogenous factor on product launch decisions. In the case of endogenous factors, the ones that lead to shorter product development duration also leads to faster manufacturing cycle time ramp-up. On the other hand, in the case of exogenous factors, the ones that lead to shorter product development duration will also lead to slower cycle time ramp-up.

Since in the case of exogenous factors, there is no change in the way the manufacturing firm deals with design or manufacturing problems; even when shorter product development leads to higher net revenue through increased revenue, the model still suggests that manufacturing ramp-up at a slower rate to avoid high manufacturing cost from increased latent issues.

However, in the case of improving endogenous factors, the firm has become more capable of dealing with problems during product development and/or manufacturing. Therefore, the firm can shorten product development and manufacturing cycle time ramp-up at the same time.

In Figure 5-19 and Figure 5-20, the optimal product development duration and ramp-up time (defined as the duration from the beginning of manufacturing until cycle time reaches full speed) under influence of exogenous factor (profit margin) and endogenous factor (rework probabilities) are illustrated, respectively. For both factors, the change in product development duration dominates the change in ramp-up time. In the case of exogenous factor where it leads to shorter product development and longer ramp-up time, the total time the start of product development to the first day of full-speed manufacturing is still longer than the base case.

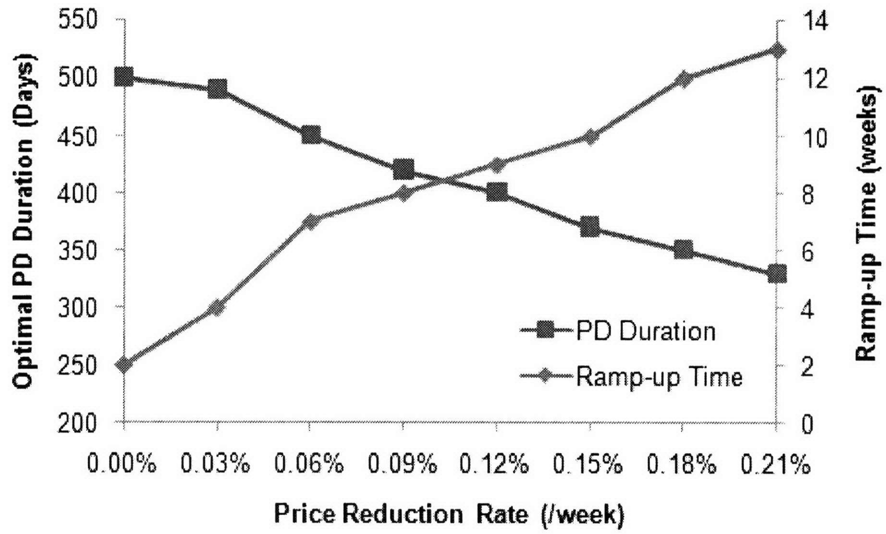

Figure 5-19: Optimal Product Development Duration and Ramp-up Time under various Price Reduction Rates (Exogenous Factor)

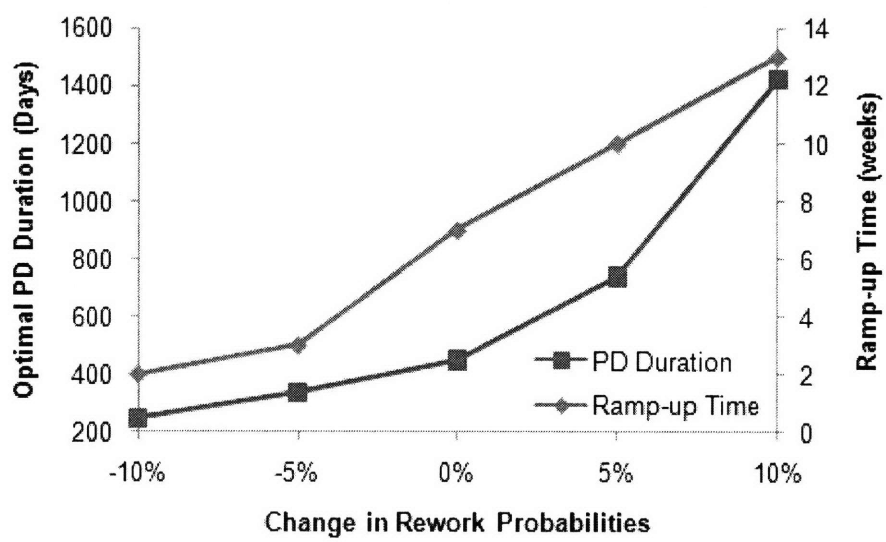

Figure 5-20: Optimal Product Development Duration and Ramp-up Time under various Changes in Rework Probabilities (Endogenous Factor)

This difference in the effect indicates that while it is important for a firm to be able plan product launch decisions based on various outside influences, it is even more important to increase its efficiency in dealing with latent issues during the design and manufacturing processes.

5.3.2 Firm Product Launch Tactical Strategies

A manufacturing firm can use the results discussed in sections 5.1 and 5.2 to not only carefully plan product launch decisions on an operating level, but also to prioritize and focus on a more tactical level of decisions that lead to improving the 'optimal' product launch decisions.

5.3.2.1 Standardization

As mentioned, variation in product development, while beneficial in the beginning, can be equally detrimental if not managed properly: different product designs in the beginning presents team with alternatives to satisfy customer demand, but the longer the team works in parallel on multiple alternatives, the more wasteful time there will be. In order to minimize such work, firm needs to standardize the process of design and process. This will minimize engineering changes that can also lead to reworks on other activities and resource waste.

There are three categories of standardization: design, process, and skill-set. (Morgan and Liker 2006) Design standardization is standardization of component design and architecture. This includes the use proven, standard components shared across multiple product models, or build model variations based on a common platform, and designing reusable architectures. Process standardization involves standardizing tasks, work orders, and the sequences of tasks in the development, testing, and manufacturing of the product. Finally, skill-set standardization involves the training of workers across different teams to reduce the amount of task variations from product development, and also helps manager to have flexibility in staffing.

In applying design standardization, common architecture and reusing of qualified components and subsystems are important to efficiency and quality since they can substantially reduce variability during product development, tooling development, and manufacturing. Without sacrificing product differentiation between generations, common components can be used in systems that do not affect customer perception of differentiation while attain proven geometries and manufacturability.

Using process standardization, the firm can standardize common product development activities, sequence of activities, and activity durations to minimize variations in information between them to reduce rework. This also helps other interdependent processes know what information is required from each other and when they are needed, preventing delay in other downstream activities.

By standardizing skill sets of team members, the firm can build team integrity and drive task variation out of product development process. Managers will have greater flexibility in assignments and more confidence in performance expectations.

By efficiently using standardization in product development and manufacturing, the firm will have flexibility in resource management, eliminate unnecessary and wasteful reworks, and achieve more effective product development and manufacturing.

5.3.2.2 Learning and Training

As Morgan mentioned "Human learns; machine does not," (Morgan and Liker 2006) it is important for managers to understand the significant of learning and training to product launch.

Learning from experience is enhanced by repetition, which is especially true for complex tasks. In product development, engineers acquire experience through multiple cycles of works. Therefore, in a firm with long product development duration, engineers have less chance to experience as many cycles of product development as in a firm with short product development duration. Therefore, there is even more benefit for a firm to shorten product development, besides the competitive advantage of releasing the product earlier.

However, there are many reasons the learning from experience process can fail. Time pressures can limit the amount of learning the worker can benefit from by limiting time to reflect on previous mistakes. Excessive workload can drown the workers, preventing them from applying lessons learned to benefit the project. Even in coming up with lessons learned, the event can turn into a blame game at which people can become reluctant to discuss problems. (Garvin 2000)

By training workers not only in their skills required to do the job, but also in positive thinking and constructive, learning-induced working culture, a team can become more effective in its learning and reduce the time needed to 'reinvent the wheel.' This will lead to faster latent issues elimination rate, both during product development and manufacturing, speeding up 'optimal' product development duration and ramp-up.

6 Conclusions and Future Opportunities

6.1 Conclusions

The feasibility of constructing a net revenue model of product launch that takes into account the performance of product development, manufacturing, and product quality has been established. The analyses performed have shown suboptimal decisions will result if manufacturing decisions are made without considering the cascading effect from product development through manufacturing and the resulting impact on product quality.

Manufacturing managers can make specific operational-level decisions, such as the product development duration and the manufacturing ramp-up timing that can influence the profitability of the product/firm, while there may be pressure to start production early and ramp up production volume quickly to generate revenue in the short term, the manager must consider the downside of these decisions. Overly shortened product development lead to a product design with unacceptably high numbers of latent issues that cause manufacturing problems. Furthermore, ramping up production volume and cycle time too fast can further compound the problem, causing even more manufacturing events. These events lead to downtime, rework, and rejected parts which increases manufacturing costs.

Not only do short product development durations and fast manufacturing ramp-ups lead to increased manufacturing costs, but also to firm's selling lower quality product at a high rate. Since there are more latent issues in the product design, combined with the high volume due to fast ramp-up, the implication of low product quality is further complicated.

On the cost side, low quality products have multiple hidden defects that can manifest at the customers as faults. Customers will bring the products in to get them serviced or parts replaced, adding to the warranty costs for the firm. On the revenue side, selling low quality products has impacts on the reputation of the firm. Firms with a reputation for high quality products can sell their products at a higher price, regardless of the actual product quality, but not without an eventual downside impact on their reputation. Selling high volumes of low quality products early in the product lifecycle can effectively destroy the firm reputation and prevent subsequent products from selling at a price they might otherwise command, even if the actual product quality improves.

Factors, both endogenous and exogenous, can have significant effects on product launch performance. A firm can take product launch improvement up to a higher level by improving product development and manufacturing operations, which influence endogenous factors such as firm strategy to improve the initial latent issues or manufacturing learning.

Improvements in product development can immensely help facilitate product launch in the manufacturing phase. By intentionally limiting the changes in product design to a set of features or parts, product development team can limit the number of latent issues in the product. This also helps the team focus their efforts on the redesigned parts from which most latent issues will be generated. This leads to fewer initial latent issues and faster issues resolution during product development, allowing manufacturing launch to start earlier without an increase in latent issues. In addition, independent of re-use, a firm that develops superior skill in identifying and resolving problems has an enormous advantage in competition. Hiring, training, retention and processes for working effectively together are possible ways to achieve this goal. The improvement allows the manager to shorten both the product development and manufacturing ramp-up and substantial increase in firm's profitability.

Improvement in manufacturing learning can also make a difference in product launch. Increased rates of manufacturing learning result in increased issue elimination during production. This allows the cycle time ramp-up to occur at a faster rate and the manufacturing launch to start earlier since the increase in latent issues typically experienced with these actions will be offset by the increased issue elimination rate. Therefore, improved manufacturing learning allows a manager to shorten the product development cycle and to ramp-up the manufacturing process more quickly.

Exogenous factors involving the market and competitors such as decaying prices, changing starting prices, different product failure rates, and different initial firm reputations can also influence the effectiveness of product launch decisions. Faster decaying prices force shorter product development durations and faster manufacturing ramp-ups so that the firm can sell more products at the high prices which are available only early on. High starting prices also allow shorter product development cycles because the product costs become less important than revenues in the net revenue calculation; the firm wants to make and sell products as early as possible to take advantage of the high prices and high profit margins. Higher product failure rates will force managers to delay manufacturing launch in order to allow sufficient time in product development to eliminate more issues since higher failure rates will reduce the 'acceptable' amount of latent issues at manufacturing launch. Finally, a higher initial firm quality reputation allows the manager to start the manufacturing launch sooner since a good quality reputation means the firm can command a higher price for the product. The firm will, therefore, want to start the production early and ramp up quickly to take advantage of the high demand and price resulting from the firm's good reputation.

To achieve the most effective product launch decisions, a manager must consider all the aforementioned factors in order to balance the benefits and penalties from changing the product development duration and the manufacturing ramp-up strategy. A firm needs to carefully consider design strategies for new product generations, weighing tradeoffs between focused and incremental design changes with smoother product launches and more radical and far reaching design changes that have extra customer appeal, but more complex launches. The manufacturing team can also help improve product launch by improving manufacturing learning and the root cause investigation process to shorten product development duration, speed manufacturing ramp-up, and improve product quality.

6.2 Contributions

The dissertation introduces an integrative model of translating product development duration and manufacturing ramp-up into product launch performance and optimizing the duration of both of them. The concept of modeling a causal connection between product development and manufacturing is introduced by modeling the impact of latent issues in product development, manufacturing, and product quality.

An innovative method of design structure matrix simulation is employed to determine the number of latent issues from product development by modifying its termination condition from the completion of all activities to a preset duration.

The number of latent issues is translated to the amount of manufacturing events through the combination of probability that an issue turns into a manufacturing event and the production volume, both of which are dependent on the cycle time decision. Furthermore, the model proposes a more straightforward manufacturing learning model by assuming that for each manufacturing event, there is a probability that the root cause of the event is eliminated. This will reduce the number of latent issues in the product design, leading directly to the reduction in number of manufacturing events and manufacturing cost.

The dissertation further proposes that the implication of product quality to product launch performance be incorporated. There may be defects that may not manifest as events during manufacturing, and therefore cannot be corrected, and remain in the finished products. The Weibull distribution is used to model the likelihood that the remaining defects show up as faults during the usage of the product. The defects will cost the firm additional warranty to replace or repair the faults.

The concept of reputation is introduced into the model to capture the effect of market imperfect information on the selling price of the product. Instead of the customer demand depending on the actual product quality, as modeled by the number of faults over the product warranty period, the demand depends on the firm's reputation. The firm reputation, while dependent on the history of product sales and quality, is not a direct representation of the current product quality. Therefore, firm should consider the product quality more carefully since it has a long-lasting effect on reputation and profitability.

Finally, case studies based on automotive industry data show that while exogenous factors have opposite effects on product development duration and manufacturing ramp-up, internal factors leads to similar results for both product development duration and manufacturing ramp-up. The robustness of the results are also shown in the studies, where late product launches less sensitive to changes in quality and reputation and early product launches are less sensitive to changes in pricing.

6.3 Future Research Opportunities

6.3.1 Effect of Uncertainty on Product Launch Decisions

While Chapter 5 explores the sensitivity of product launch decisions to various endogenous and exogenous factors, the model has yet to fully incorporate uncertainty into calculating product launch decision performance. It would be beneficial to understand not only how the average value of a factor, but more generally how its distribution affects the performance of a decision.

Some of the factors that can be affected by uncertainties are selling price, demand, product failure rate, and initial reputation. For example, the firm cannot be fully certain at the beginning of the manufacturing launch what the competitors and overall economy will do, and therefore cannot know the price, and consequently, the demand the product will obtain.

The uncertainty in selling price stems from the many uncertainties in the market: level of competition, imperfect information, and customer demand. The firm has no way of exactly measuring how much the customer knows about its products, the accuracy of that information, or how its product compares to other firms' products. Even with that, each customer values different features of a product differently. For example, one customer might value a computer with good graphics capability, while another might value a computer with good audio output and all of these might change because of various uncontrollable factors. Therefore, it is difficult for the firm to expect how the products would perform once it is released in the market, both in short term and throughout its lifecycle.

Uncertainty of firm reputation can affect the product launch decision performance. As shown in Figure 4-7, the effect of reputation on the product price is asymmetric; an increase in price from increased reputation is not equal to the decrease in price from decreased reputation of the same degree. In fact, the magnitude of increase is about half of the magnitude of decrease, for the same change in reputation. Consequently, firms should be even more careful about any negative impact on reputation, as there is more to lose than to gain with reputation uncertainty.

Monte Carlo simulation can help facilitate such analyses. By randomly generating inputs based on specified probability distribution functions, the model can take the inputs and generate the net revenues based on fixed product development duration and ramp-up. The net revenues can then averaged and that is the expected net revenue for that product development duration. The optimal product launch decision is the one that results in the highest expected net revenue. Furthermore, the robustness of product development duration and cycle time ramp-up can also be investigated by studying the resulting distributions of costs and revenues, or even the elements of cost such as material cost, labor cost, or warranty cost.

6.3.2 Reputation Definition

In this dissertation, reputation is defined as the product of sales rate and quality index. The quality index is a term that represents the comparison in product failure rates between an average value and the product. However, there are other references in the literature that suggest reputation has more to do with of the quality of the products and less with the number of products sold. (Shapiro 1982; Shapiro 1983; Paulson Gjerde and Slotnick 2004)

Keeping other relationships the same, this conceptual change in the way reputation is modeled could lead to product quality affecting product launch performance more significantly. There would be fewer reasons to shorten product development and ramp up the volume other than to obtain more total revenue. With revenue per vehicle depends only on reputation, and reputation depends only on the history of quality, product quality now becomes an even stronger driver for revenue. The firm will have to give even more priority to selling high quality products to achieve high reputation and make profit.

6.3.3 Manufacturing Industry Taxonomies

According to the work by Kar (2007), a manufacturing industry can be categorized by two characteristics: material intensity and capital/labor intensity. In his work, a manufacturing business is categorized as either material intensive or non-material intensive and either labor intensive or capital intensive.

While the details of the classification scheme are subject to debate, material intensity and capital/labor intensity do not need to be defined in discrete fashion. In fact, both material and capital/labor intensities can be defined as the degree of intensities, i.e. material intensity by the percentage of material cost in unit cost and capital/labor intensity by the ratio of labor cost to capital cost per unit.

Material intensity, by definition, will affect the material cost in the product. Material cost in product launch model is driven by the reject rate, which is driven by number of latent issues in the product design during manufacturing. The more important material cost is in a product cost, the longer product development and the slower the cycle time ramp-up should be to avoid unnecessary rejected parts which leads to high material cost. Therefore, the change in material intensity should affect product launch decisions.

Total capital cost is constant regardless of product launch decisions, and therefore to minimize the capital cost per unit, a manager will want to shorten the product development cycle and speed up the manufacturing ramp-up. However, this benefit is offset by the increase in latent issues, which leads to low product quality. Total labor cost, on the other hand, is affected by product launch decisions through the use of overtime. While not all product launch decisions will lead to overtime, increasing labor intensity will further prevent any product launch decisions that lead to overtime. This will drive the manager to lengthen the product development duration and slow down the ramp-up. Although this will lead to the issue of time value of money since revenue will start late. Therefore, degree of capital/labor intensity will also affect product launch decisions.

6.3.4 Product Quality Transparency

Product quality transparency is the 'ability' of the product to demonstrate its quality to the customer. It is assumed in the model that the product quality is apparent to the customer at the time of purchase. However, certain products' qualities are easily demonstrated, while others are not even after prolonged observation or usage, especially for more complex products. This product characteristic will have an effect on product launch decisions.

In equation (4.8), D parameter that represents the 'perception delay' of the customers on the product. While this can be interpreted as a delay for the firm's reputation to accurately represent its product quality, D can also be used to represent the delay of the customer perception between the time of purchase and the time the actual product quality is decided for the product. D can then represent the total perception delay from the time of product purchase to the time that the product quality impacts the firm's reputation.

The more transparent the product quality is, the faster the quality of the product impacts the firm's reputation. The firm should then lengthen product development duration to improve product quality, which would quickly results in improved firm's reputation and increase in net revenue.

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