Research Article

Investigation of Optimal Production Ramp-ups under Demand Uncertainty

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Abstract

This paper explores the effect of demand uncertainty on the decision variable of operation time and its interaction with yield and learning during production ramp-up. A dynamic profit model for production ramp-up coupled with learning and demand uncertainty is built to identify optimal ramp-ups under various manufacturing contexts. Numerical simulations are explored to determine the various factors leading to changes in optimal production ramp-ups due to demand uncertainty. Results demonstrate that, under increasing demand uncertainty, firms should generally be conservative and slow down the ramp-up. It is also demonstrated that demand uncertainty leads to slower ramp-up regardless of varying learning rates and capacity/demand constraints. The only exception is products with high profit margin in which optimal ramp-ups are insensitive to demand uncertainty.

Keywords: Demand uncertainty; Learning; Profit model; Production ramp-up.

1. Introduction

Increasing global competition means that customers are always looking for the latest model products on the market. Product lifecycles are becoming shorter while new product introduction rates have been steadily increasing. [1-6] Hence, product introduction has become an increasingly larger part to the operation of a manufacturing firm. To survive, it must succeed financially and consistently at releasing new products. However, releasing new product is not a simple act of making an announcement and putting the new products on store shelves. Before a new product can be introduced into the market, it must be introduced into a manufacturing facility.

Typically, the time it takes to make a product—the operation time—is long for the first few. As workers become more familiar with the manufacturing processes and make adjustments to eliminate unnecessary wastes, the facility can gradually speed up manufacturing until it reaches full manufacturing capacity. This progressive increase in production rate is called production ramp-up. Operation time during production ramp-up directly affects the productivity and, thus, the profitability of the firm.

At the center of a production ramp-up is the learning effect, which in this article refers to the improvement in yield as workers cumulative output increases as opposed to the traditional meaning of the reduction in unit cost. By gaining experience, workers become familiarized with the processes involved in manufacturing the new products and are less prone to making mistakes, allowing an increase in production rate. It is evident that firms in various manufacturing industries, from semiconductor to automotive [3, 7], have exhibited significant yield improvements from the learning effect during production ramp-up. If the facility is operated excessively fast, it can lead to production of

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defective parts because workers may not have sufficient time or are not yet familiar with manufacturing the parts. On the other hand, overly slow production incurred an opportunity cost from wasted capacity. Also, from a learning standpoint, operating the facility rapidly means that workers will be generating higher cumulative output, leading to faster improvement. This complex interrelationship creates an "intertemporal trade-off between the short-term opportunity cost of capacity and long-term value of learning." [8]

Another significant factor that can affect the profitability of a firm during production ramp-up is demand uncertainty. This adds a stochastic dimension to the tradeoff between the opportunity cost and the value of learning. Regardless of the amount of marketing research going into the product design, a firm may not be able to perfectly foresee the demand for its new products. When demand is underestimated, there is an additional opportunity cost of underproduction. When it is overestimated, capacity is wasted and the manufacturing facility incurs additional manufacturing costs without generating revenue. To accurately evaluate the effect of demand uncertainty to the profit stream of production ramp-up, this article have incorporated these additional costs when determining optimal ramp-ups.

This article investigates the interaction between the decision variable of operation time, yield, yield improvement or learning, and the effect of demand uncertainty throughout the production ramp-up. A dynamic profit model of production ramp-up that allows for the flexibility of periodic changes in operation time is constructed. The model uses profit to determine the optimal set of operation times—a production ramp-up—from the introduction of a new product to the period of full capacity production. Numerical illustrations are used to demonstrate the effect of demand uncertainty on the optimal production ramp-ups under various manufacturing contexts.

The remainder of the article is arranged as follows. In the next section, related streams of literature are reviewed to identify the contributions of this article. In Section 3, the dynamic, intertemporal profit model of production ramp-up is detailed along with underlying assumptions. Section 4 demonstrates the effect of demand uncertainty on the optimal set of operation times through numerical illustrations and discussions of the underlying reasons. The managerial implications and future directions for research are concluded in Section 5.

2. Related literature

This study draws on two branches of literature: process capacity improvement from learning and capacity planning under uncertainty. To better explain and position the contribution, this article has provided a more detailed review of the two branches.

There have been a number of researches addressing the importance of enhancing production capacity during ramp-up through investments, experimentation, and learning. Bayus [9] developed a dynamic model of product innovation where the tradeoffs between investments on product improvement and process improvement are considered. Research by Chand et al. [10] focused on allocating production capacity between production activities and improvement activities, such as those that go on during production launch. Optimal investments in process change and knowledge creation versus process improvement were identified by Carrillo and Gaimon [11]. Terwiesch and Xu [12] studied the tradeoff between capacity enhancement from process change and learning during production ramp-up and identified regimes where "copy-exact" and more traditional approaches to process improvement were appropriate. Carrillo and Franza [1] developed a model to determine the best time-to-market and time-to-volume (ramp-up duration) in product design and manufacturing capacity, focusing on the role of the allocation of resources between these activities. Terwiesch et al. [13] indicated that high-tech firms are shifting from minimizing time-to-market to minimizing time-to-volume and studied optimal strategies to facilitate learning during production ramp-up in the data storage industry. Terwiesch and Bohn [8] applied a dynamic programming model to explore the interactions among capacity utilization, yield, and learning to assess the net value of experimentation (and the learning it provides) during the ramp-up period. As stated, a variety of literature investigates the interaction between capacity improvement (yield) and learning, but this work builds on existing research by exploring how demand uncertainty affects the decision of optimal ramp-up.

Another branch of related work is capacity planning under demand uncertainty. The concept has been detailed in an extensive review by Mula et al [14]. Bitran and Yanesse [15] applied a deterministic approximation to a nonsequential capacity planning problem when demand is stochastic. Karabuk and Wu [16] formulated a capacity planning model using multi-stage stochastic program where demand and capacity uncertainties were incorporated. Eppen et al. [17] used stochastic programming approach to study capacity planning problems for different demand scenarios regarding facility selection. Breithaupt [18] presented a dynamic production model to develop a feedback control for capacity planning with defined control and reference variables. These articles use analytical or simulation methods to assist in capacity planning under uncertainties such as demand, quality, and lead time, while this article aims to extend the existing research by forming a linkage among capacity, operation time, and learning while addressing demand uncertainty.

The contribution of this article is to establish a connection between the two aforementioned streams of literature, an approach no studies have attempted so far. The established intertemporal linkage among operation time, learning, and capacity from the capacity enhancement research stream is combined with a methodology to determine the optimal capacity for demand uncertainty in order to determine the optimal set of operation times during the production ramp-up, referred to in this work as the optimal production ramp-up. Additionally, manufacturing contexts that influence the optimal ramp-up under demand uncertainty are also investigated.

3. Evaluating production ramp-up: an intertemporal dynamic profit model

In this section, the calculations and assumptions involved in modeling production ramp-up and evaluating its economic performance are described. First, the production ramp-up model that establishes the relationship among operation time, yield, learning, and output is explained. Next, a profit model translates the output into deterministic cost, revenue, and profit. Then, the uncertain revenue model incorporated into this work is detailed along with the optimization method used to determine optimal ramp-ups.

3.1 Dynamic Production Ramp-up Model

A production ramp-up, as mentioned previously, is a set of gradually decreasing operation times from when the new product is introduced into the manufacturing facility until the facility reaches its full production capacity. Throughout this duration, the operation time is gradually reduced to speed up the production rate. To simplify this process, the duration is divided into *n* periods of steady state operation each of which the operation time remains constant.

Assume that the total available time is T for all time periods, and that the minimum possible operation time for the process is $t_{\min}$. The maximum possible production capacity is therefore $T / t_{\min}$. This minimum operation time is related to the physical limit of the process such as the maximum speed of cutting tools or cooling time of a material. The operation time choice t_i, is a decision variable in each period, and a set of operation times $\tau = [t_1, t_2,\ldots, t_n]$ is referred to as a ramp-up. The number of product starts with the available time is thus T / t_i. Therefore, the cumulative product starts in manufacturing up to period i is

$$v_i = \sum_{j=1}^{i} \frac{T}{t_j} \quad (1)$$

Define yield y_i as the fraction of nondefective products out of the total starts in manufacturing. It is modeled as a function of operation time and manufacturing learning parameter a_i, which is the reduction in defect rate due to accumulated experience. A specific functional form relating defect rate, operation time, and manufacturing learning is defined according to Terwiesch and Bohn [8] to simplify the analysis as

$$y_i = y_0 \left(1 - a_i \frac{t_{\min}}{t_i}\right) \quad (2)$$

where $t_{\min}$ is the minimum operation time below which the operation is physically impossible. The parameter y_0 captures the base yield which is independent of the operation time and cannot be improved, while the parameter a represents the benefit of learning on the reduction of defective product rate. The parameter a is modeled using a truncated form of the log-linear relationship developed by Nadeau et al. [19]:

$$a_i = \min(a_{\max}, \max(a_{\min}, bv_{i-1}^{-q})) \quad (3)$$

where $a_{\max}$ and $a_{\min}$ are the maximum and minimum observable values for a. The parameter b is the chance of the first product being defective; v is the cumulative output; and q is the learning rate. Here, a larger value of q leads to faster yield improvement.

This functional form is consistent with the assumptions in [8] that yield should improve with increasing operation time but with diminishing returns and that yield should also improve with increasing process capability, a quantity that is captured by a. The form is different, however, in the way learning is modeled. According to [8], learning is modeled as a function of experimentation effort and the cumulative time the facility has been processing the new product, independent of operation times. In this work, learning is modeled after cumulative output, which depends on operation times of all preceding periods as shown in Eq. (3).

The number of nondefective products in period i can then be expressed as

$$N_i = \frac{T}{t_i} y_0 \left(1 - a_i \frac{t_{\min}}{t_i}\right). \quad (4)$$

3.2 Deterministic Profit Model

Early in production ramp-up demand for the product is high, but this will decrease over time as the product gradually loses its 'new' appeal. Therefore, it is assumed that the starting demand is d, and it decays at a rate of δ per period. For simplicity, since the reduction in revenue stream due to this 'loss of appeal' can be modeled using δ, the selling price p is assumed constant. As this article focuses on the dynamics inside the manufacturing facility, it is viewed that the demand and its decay rate are exogenous to the model. If demand in a period is higher than the number of nondefective products, it is assumed that customers will not wait for products at a later period as there can be many other similar products available. Only the number of products made to meet demand in each period is sold; unmet demand is irrecoverable. The number of surplus products, which are stored for later sale, is represented by S_i. The number of products sold, s_i, in period i is

$$s_i = \min\left(d\delta^{i-1}, N_i + S_{i-1}\right) \quad (5)$$

where the first term is the demand in period i. The second term is the number of products available for sale in the same period, equal to the number of nondefective products in the period plus the number of surplus products from all preceding weeks. The number of surplus products at any period can be recursively defined as

$$S_i = \begin{cases} 0 & ; i = 0 \\ S_{i-1} + N_i - s_i & ; 0 < i \leq n \end{cases}. \quad (6)$$

A variable cost per product start is c. Therefore, the deterministic profit generated in each period is

$$\pi_i = ps_i - c\frac{T}{t_i}. \quad (7)$$

Based on Eq.(4), it would seem straightforward to derive the operation time that maximizes the number of nondefective products in a period. However, as learning is dependent on the cumulative output and thus the operation time, all subsequent period operation time decisions are dependent on the current period decision. The optimal operation time for a period is not necessarily the one that maximizes the profit in this period. In fact, it may be an operation time that generates more learning from which future periods may benefit.

The added complexity of considering demand is that the number of products sold is no longer singly dependent on the operation time decision. When manufacturing is constrained by demand, decreasing operation time increases the revenue until production volume exceeds demand. Beyond this point, faster operation time only leads to product surplus which needs to be stored for sale later.

The deterministic total profit is the discounted profit streams over production ramp-up periods. Taking r as the discount rate, the deterministic total profit is

$$\Pi_d(\tau) = \sum_{i=1}^{n} \frac{\pi_i}{(1+r)^i}$$
$$\text{where } \tau = [t_1, t_2, ..., t_n]. \quad (8)$$

The operation time choice in a given period affects the profit in two ways. First, it affects revenue through its relationship with yield and nondefective output. For the operation time choice to maximize the revenue, it must maximize the number of nondefective output. Second, it affects the costs in subsequent periods as they depend on learning and cumulative output.

However, if demand is lower than capacity, then revenue depends on the operation time choice until the nondefective output reaches the demand. Beyond this point, reducing the operation time to generate additional output does not increase revenue, but the additional output would still enhance learning.

3.3 Incorporating Demand Uncertainty

This article assumed that the starting demand is no longer a deterministic value d_0 but instead a randomly distributed number with an average of μ and a standard deviation of σ:

$$d \sim N(\mu, \sigma^2). \quad (9)$$

The demands for subsequent weeks still follow the functional form applied in the deterministic model with a constant weekly decay rate of δ. The magnitude of uncertainty in demand is captured by its standard deviation, which represents the accuracy of demand forecast. Instead of evaluating a ramp-up's performance by the total profit based on Eq. (8), the objective function is now an expected value of the total profit based on the distribution of demand. The expected value of profit in period i is the revenue from expected sales minus the cost:

$$E[\pi_i] = pE[s_i] - c\frac{T}{t_i}. \quad (10)$$

The objective function to be used to search for the optimal ramp-up is the discounted expected profit stream over the production ramp-up periods. Taking r as the discount rate, the objective function becomes

$$\Pi_u(\tau) = \sum_{i=1}^{n} \frac{E[\pi_i]}{(1+r)^i}. \quad (11)$$

In this article, the objective function for the deterministic demand cases is the total profit defined in Eq. (8) while the objective function for the uncertain demand cases is the expected total profit defined in Eq. (11). Crystal Ball, an Excel add-on, is used in conjunction with its OptQuest module to generate demand uncertainty and to search for optimal ramp-ups. Two constraints are imposed on the operation times: 1) that they are non-increasing, i.e., the operation time of the current week is smaller than or equal to that of the preceding period and 2) that they are integers. These conditions are imposed to imitate a typical production ramp-up that gradually increases production rate and to reduce the running time of the search algorithm. For each scenario, the simulation is repeated at least 100000 times to ensure that the confidence intervals are sufficiently small and that the differences in expected profits among the cases are statistically significant. The 95% confidence interval bars are shown on all numerical illustration cases in the next section as error bars.

4. Numerical Illustrations

4.1 Baseline Parameters

A number of numerical examples are solved in this section to provide a better understanding of optimal ramp-ups in various manufacturing contexts. Consider a typical automotive underbody manufacturing facility. The discount rate is 0.3% per period. The cost per start c is \$500. The available manufacturing time T is 80 hours per period. The minimum possible operation time $t_{\min}$ is 60 s, which means that the maximum production capacity is 4,800 vehicles per period if there is no defective product at all. The starting demand is assumed to be normally distributed with an average of 4,800 vehicles per period with a decay parameter δ = 0.95, and the magnitude of demand uncertainty is modeled by its standard deviation. The finished product is sold at \$750 so that the ratio p/c—indicative of the product profit margin—is 1.5. According to the data from manufacturing experts, there are minimal yield losses during steady state operation (y_0 = 1) and learning parameter b = 0.8 and q = 0.15. This baseline scenario is modeled after an actual midsize sedan automotive underbody plant. The illustrative cases are solved using Monte-Carlo simulation to model the demand and the OptQuest module in Crystal Ball to find the optimal ramp-ups.

4.2 Optimal Ramp-ups and Profitability

First, this article investigates the effect of demand uncertainty on optimal ramp-ups. Fig.1 exhibits typical suggested ramp-ups for the baseline case under increasing standard deviations (SD) of starting demand. The operation times in the early weeks are long and gradually decreasing as workers accumulate experience and become more efficient with the manufacturing processes so they can produce more and increase profit.

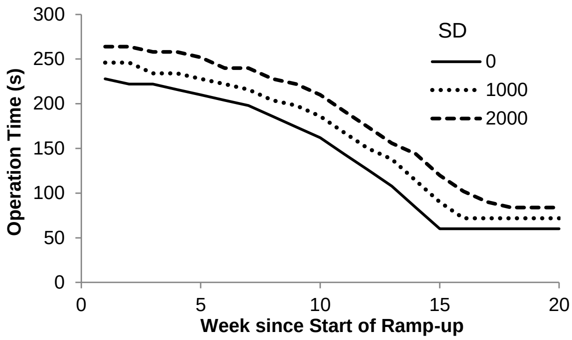

Fig.1. Comparison of optimal ramp-ups under demand uncertainty.

More importantly, Fig.1 demonstrates the effect of demand uncertainty on the optimal ramp-ups. As demand becomes more volatile and unpredictable, the model suggests increasingly slower ramp-ups. The cumulative outputs after week 20 of the suggested ramp-ups of SD = 0, 1000, and 2000 are 42942, 35598, and 29697, respectively. This means that under the given manufacturing context, the opportunity cost is low compared to the risk of unsold products. This result is in agreement with that of Anupindi and Jiang [20]. Increasing demand uncertainty leads to increasing risk and lower value for each additional nondefective product. Therefore, the model suggests slower production ramp-ups with increasing demand uncertainty. This is illustrated in

Fig. **2**. Note that from this figure onward, each optimal ramp-up will be represented as an average operation time over production ramp-up (20 weeks). This is to avoid overcrowding the figures and allow for easy ramp-up comparison.

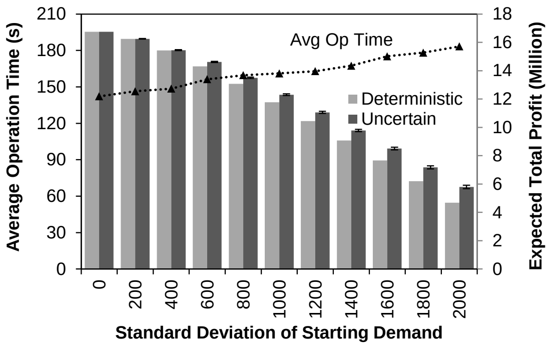

Fig. 2. Expected value of profits of deterministic and uncertain optimal ramp-ups and profit improvement under demand uncertainty.

The difference between the expected profits for deterministic and uncertain cases is the 'value' of explicitly considering demand uncertainty. Notice that the differences are statically significant only beyond the standard deviation of 600. Therefore, this approach is not applicable for relatively predictable demands.

As demand uncertainty increases, the difference widens while expected profits decreases, showing that the 'value' becomes exponentially more significant with large demand uncertainty. In this case, at standard deviation of 2000, the expected improvement in total profit is $1.5 million or 33% of the expected total profit from deterministic ramp-up. The increase in average operation time between standard deviations of 0 and 2000 is 31 s or 22%.

4.3 Demand-constrained Systems

Section 4.2 investigates a system whose maximum capacity equivalent to the demand so that all nondefective products are sold, which raises a question of whether the suggested slower ramp-up is simply a result of this condition. This section will attempt to answer that question. Consider a case where the average starting demand (2400) is much lower than the maximum capacity (4800). In other words, the system is constrained by demand. Here, the comparison to section 4.2 is made among cases with equal coefficients of variation to account for the differences in average starting demands. For the baseline case, the average starting demand is 4800, and its standard deviations are 200, 400, …, 2000. Therefore, to make a fair comparison, the standard deviations of starting demand in this case will be 100, 200, …, 1000, thus keeping the same coefficients of variation.

Similar to the baseline case, increasing demand uncertainty also leads to slower optimal production ramp-ups as shown in Fig. 3. The increases in average operation times from the deterministic to the most uncertain demands are also comparable (28% vs 30%), exhibiting that demand and capacity constraints have very little effect on the optimal ramp-ups under demand uncertainty.

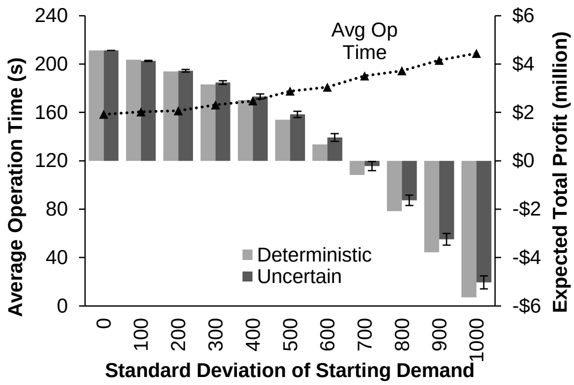

Fig.3. Average operation times under varying demand uncertainty for a demand-constrained production (average starting demand = 2400).

Fig. 3 also illustrates that demand uncertainty can be so great that the resulting expected value of profit is negative—from the standard deviation of 600 and above in this case. With increasing demand uncertainty, it becomes more likely that the firm will incur losses. Therefore, selling price should be carefully determined especially when manufacturing is demand-constrained. To shed some light on the pricing decision, this work will further investigate the effect of product profit margin on optimal ramp-ups.

4.4 High Product Profit Margin

This article now considers a case for a production ramp-up of a high profit margin product—where the ratio of selling price to cost per start is high (*p/c* = 5), compared to the baseline case (*p/c* = 1.5). As shown in Fig**.4.** Average operation times under varying demand uncertainty for a low profit margin product (*p/c* = 5)., the most contrasting aspect of the result compared to low profit margin cases in sections 4.2 and 4.3 is that the optimal ramp-ups for high profit margin cases are virtually insensitive to demand uncertainty. The model suggests the same ramp-ups for both deterministic and uncertain cases, resulting in identical expected total profits. This is because the selling price is high and the loss of sale has a higher value than the cost of unsold finished product; maximizing expected profit becomes a simple matter of maximizing the number of finished products, regardless of demand. Therefore, increasing demand uncertainty does not affect the optimal ramp-ups of high profit margin products.

4.5 Fast Learning Rate

Since learning is such a central process to production ramp-up, exploring how it is affected by learning rate under demand uncertainty can prove beneficial. In this section, the learning rate *q* has been increased from 0.15 in the baseline case to 0.3. In the baseline case, it is found that the model suggests increasing average operation time by 11.3% as demand uncertainty increases. Fig.5 exhibits the change in average operation time with increasing demand uncertainty for a fast learning firm.

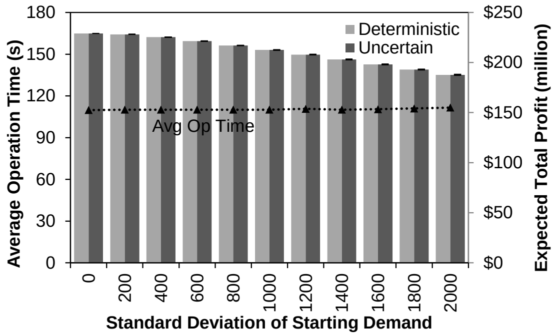

Fig.4. Average operation times under varying demand uncertainty for a low profit margin product (*p/c* = 5).

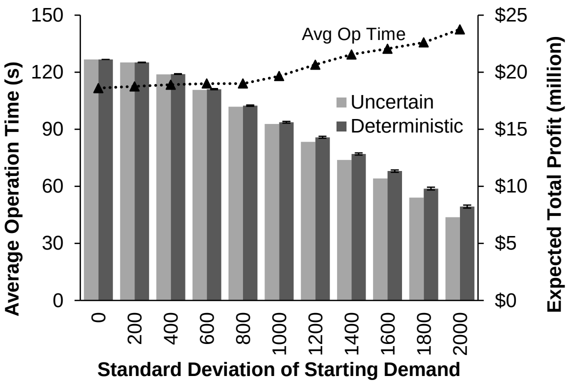

Fig.5. Average operation times under varying demand uncertainty with respect to different learning rates.

Compared to the baseline case, the model suggests increasing average operation time by 30 s or 27%. Note that the suggested increases in average operation times are the same; the percentage increase is more for a fast learning firm only because its average operation time is smaller. The expected total profit increases by $0.9 million or 13% for the case with a standard deviation of 2000. Here, a fast learning firm stands to gain less from considering uncertainty because it already operates with fast improvement and little loss, so there is little room for improvement even with a slower ramp-up.

5. Conclusion

The article presents the findings on the effect of demand uncertainty on optimal production ramp-ups under various manufacturing contexts. By developing a dynamic profit model of production ramp-up that incorporates learning and uncertain demand, optimal ramp-ups can be identified through expected profit maximization. The findings shed light on the robustness of suggested optimal ramp-ups under the effects of varying profit margins and learning rates.

Numerical illustrations demonstrate that, in certain manufacturing contexts, explicit consideration of the stochastic nature of demand can be crucial to the financial performance of production ramp-up. This is especially true for production of low profit margin products with slow learning rates. Additionally, this emphasizes the advantages of manufacturers whose profit margins are high—they do not need to be concerned with demand uncertainty. They only have to maximize nondefective output to achieve optimum financial performance.

The constraints on production, whether it is made upon capacity or demand, have no effect on the changes in optimal ramp-ups under demand uncertainty. Change in profit due to capacity utilization is unaffected by demand, resulting in similar changes in optimal ramp-ups regardless of the constraints.

Product profit margin is crucial to the robustness of the optimal production ramp-ups under demand uncertainty. For low profit margin products, managers should consider slowing down the ramp-up as demand becomes increasingly uncertain. For such a case, cost saving is the way to increase expected profit. On the contrary, optimal production ramp-ups for high profit margin products are virtually insensitive to demand uncertainty; generating profit is easily achieved by producing more products to satisfy demand since the cost per start is not expensive.

Manufacturing learning rates have a less significant impact than profit margin. A fast learning system is more affected than a slow learning system as it ramps up operation time faster, so there is more room to slow down the system, save cost, and still be able to satisfy demand.

This article has investigated in details the robustness of optimal production ramp-up due to demand uncertainty. Future research should address uncertainty in factors that affect cost structure of production. It may also be worthwhile to explore uncertainties that affect cost and revenue simultaneously, and to investigate if there exists a synergy between them.

6. Acknowledgment

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7. References

[1] Carrillo, J.E. and R.M. Franza, *Investing in product development and production capabilities: The crucial linkage between time-to-market and ramp-up time*. European Journal of Operational Research, 2006. 171(2): p. 536-556.

[2] Iansiti, M. and J. West, *Technology Integration: Turning Great Research into Great Products.* Harvard Business Review, 1997. 75(3): p. 69-79.

[3] Ceglarek, D., et al., *Time-Based Competition in Multistage Manufacturing: Stream-of-Variation Analysis (SOVA) Methodology—Review.* International Journal of Flexible Manufacturing Systems, 2004. V16(1): p. 11-44.

[4] Sherman, J.D., W.E. Souder, and S.A. Jenssen, *Differential effects of the*

primary forms of cross functional integration on product development cycle time. Journal of Product Innovation Management, 2000. 17(4): p. 257-267.

[5] Griffin, A., *Modeling and measuring product development cycle time across industries*. Journal of Engineering and Technology Management, 1997. 14(1): p. 1-24.

[6] Ottosson, S., *Dealing with innovation push and market need*. Technovation, 2004. 24(4): p. 279-285.

[7] Cunningham, S.P., C.J. Spanos, and K. Voros, *Semiconductor yield improvement: results and best practices*. Semiconductor Manufacturing, IEEE Transactions on, 1995. 8(2): p. 103-109.

[8] Terwiesch, C. and R.E. Bohn, *Learning and process improvement during production ramp-up*. International Journal of Production Economics, 2001. 70(1): p. 1-19.

[9] Bayus, B.L., *Optimal dynamic policies for product and process innovation*. Journal of Operations Management, 1995. 12(3-4): p. 173-185.

[10] Chand, S., et al., *Capacity allocation for dynamic process improvement with quality and demand considerations*. Operations Research, 1996. 44(6): p. 964-975.

[11] Carrillo, J.E. and C. Gaimon, *Improving Manufacturing Performance Through Process Change and Knowledge Creation*. Management Science, 2000. 46(2): p. 265-288.

[12] Terwiesch, C. and Y. Xu, *The copy-exactly ramp-up strategy: trading-off learning with process change*. Engineering Management, IEEE Transactions on, 2004. 51(1): p. 70-84.

[13] Terwiesch, C., R.E. Bohn, and K.S. Chea, *International product transfer and production ramp-up: A case study from the data storage industry*. R & D Management, 2001. 31(4): p. 435-451.

[14] Mula, J., et al., *Models for production planning under uncertainty: A review*. International Journal of Production Economics, 2006. 103(1): p. 271-285.

[15] Bitran, G.R. and H.H. Yanasse, *Deterministic Approximations to Stochastic Production Problems*. Operations Research, 1984. 32(5): p. 999-1018.

[16] Karabuk, S. and S.D. Wu, *Strategic capacity planning in the semiconductor industry: A stochastic programming approach*. Department of lndustrial and Manufacturing Systems Engineering, 1999.

[17] Eppen, G.D., R.K. Martin, and L. Schrage, *OR Practice—A Scenario Approach to Capacity Planning*. Operations Research, 1989. 37(4): p. 517-527.

[18] Breithaupt, J.W., *Controlling production dynamics-managing uncertainties with automatic production control*. International Journal of Production Research, 2000. 38(17): p. 4235-4246.

[19] Nadeau, M.-C., et al., *A dynamic process-based cost modeling approach to understand learning effects in manufacturing*. International Journal of Production Economics, 2010. 128(1): p. 223-234.

[20] Anupindi, R. and L. Jiang, *Capacity investment under postponement strategies, market competition, and demand uncertainty*. Management Science, 2008. 54(11): p. 1876-1890.