Improving Production Yield through Learning by Doing and Knowledge Sharing

Thomas A. Roemer
Rady School of Management
University of California, San Diego
La Jolla, CA 92093
troemer@ucsd.edu

Hasan Arslan
Sawyer Business School
Suffolk University
Boston, MA 02108
harslan@suffolk.edu

Ali Yassine
Industrial & Enterprise Systems Engineering
University of Illinois at Urbana-Champaign
Urbana, IL 61801
yassine@uiuc.edu

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Abstract

This paper addresses the production ramp-up for products with low initial yields. Our principal focus is on when to switch over from pilot production to full production using all available capacity. In a first model, we introduce a manufacturer with only one production line, or equivalently with n independent lines, where all learning is autonomous, based on cumulative production volumes. Under very general assumptions, we show that, in this scenario, pilot production is never optimal and that switch-over simply occurs when the margins of the new product exceed those of the old product.

In a second model, we allow for knowledge transfer between lines in addition to autonomous learning. We distinguish between process focused manufacturers, who strive for a high degree of similarity between product lines, such as Intel's copy exactly strategy and skill focused manufacturers, whose strength lie in their employees' skills of learning autonomously. We show that switch-over decisions can no longer be myopic, but must take future product margins as well as the focus orientation of the manufacturer into account. Skill focused manufacturers should introduce their products earlier and must react differently to competitive pressures than process focused manufacturers.

Keywords: Yield Improvement, Learning by Doing, Knowledge Sharing, Pilot Production, Product Introduction, Skill Focus, and Process Focus.

1 Introduction

Fierce competition and rapid innovation force many firms to introduce new products at ever increasing rates and often times before the underlying production processes and technologies are fully understood. Initial production yield levels are therefore frequently very low, with single digit yield levels not being uncommon (Dolinsky et al., 1990, Leachman and Berglund, 2003). As production continues, production process problems are identified and solved, and employees gain better understanding of the production process. Bottlenecks are identified and circumvented, machine down-times are minimized, root causes are identified, and best practices are slowly established, leading to a steady increase in production yield levels over time.

Improvements in production yields play an important role in profitability of a firm. For instance, if demand outstrips capacity, a 1% increase in production yield for a semiconductor fab producing $20,000$ wafers per month with an average selling price of $\$2,000$ per wafer can result in additional $\$4.8M$ revenue in a year. Moreover, the additional revenue is almost entirely profit, since only post production (i.e. storage and distribution) costs need to be covered by it. Conversely, in industries characterized by overcapacity, high yield rates are an important tool in securing market share. In particular, high yield producers have an inherent cost advantage over their competitors, have a lower risk of delivering bad quality and can more quickly accommodate customer requests. A thorough understanding of the dynamics of production yields is therefore paramount for successful and profitable introduction of new products (Bohn and Terwiesch, 1999).

This paper attempts to shed some light on how to efficiently manage production yields. In particular, we look at two opportunities for improving yields: through *learning by doing* on individual production lines and through *knowledge transfer* between multiple production lines. With learning by doing, a production line continues to learn and refine the recipes and tools for production through the accumulation of knowledge. New knowledge is obtained, albeit typically at a decreasing marginal rate, with every unit produced. This knowledge translates into improved processes and ultimately higher yields. However, this knowledge remains germane to the production line, unless it can effectively be transferred to other production lines as well. The potential to transfer knowledge is limited, if production lines differ considerably from each other, but is greatly enhanced the more the production lines resemble each other. For example, by standardizing equipment and processes among different fabs through its famous *copy exactly* strategy, Intel is able to efficiently transfer knowledge and exchange engineers across production lines (Clark, 2002). But even more traditional manufacturers such as Visteon follow suite by standardizing equipment and processes across manufacturing facilities to enable better knowledge sharing (National Instruments, 1999).

In managing learning by doing, a principal question is how much capacity to allocate to a new product for the purpose of gaining knowledge about efficient processing and increasing yield rates. Typically, the required capacity is taken from the current production line with high yields and profit margins, giving rise to a trade-off between continued profits from the current product line and higher future profits through accelerated learning for the next product. We refer to the period where only a limited amount of capacity is dedicated to the new product, as *pilot production* versus *full production* for the case when all available capacity is dedicated to the new product. Knowledge transfers, on the other hand, can consume a tremendous amount of resources. For example, exchanging workers across production lines, holding team meetings, and composing benchmarking reports can be quite costly, and their costs have to be compensated by corresponding yield increases.

To provide insights into the dynamics of production improvement during ramp-up, this study considers a manufacturer that introduces successive generations of products, possibly on multiple production lines with similar production processes and aims at answering the following two questions. First, under what circumstances is pilot production desirable and how much capacity should be allocated to pilot production? Second, when should full production of the new product commence and what drives the timing for full production?

The remainder of the paper is organized as follows. Section 2 reviews the extant literature. Section 3 considers the case without knowledge transfer, in particular the case with only one production line. We analyze how to split production between the new and old product to maximize total profits, considering that the new product typically faces low initial yields. We show that, in this case, pilot production is never optimal, and either the old or the new product is produced on the existing lines, but not both concurrently. In Section 4, we extend our view to multiple similar production lines where acquired knowledge can be passed on across production lines. We determine conditions under which launching pilot production becomes preferable based on a firm's focus. In particular, we distinguish between two types of focus: *Process focused* firms emphasize a high degree of similarity between production lines, whereas *skill focused* firms primarily rely on their employees' abilities to learn autonomously. We conclude the paper in Section 5 by summarizing our main findings and pointing out potential limitations of our approaches.

2 Literature Review

The work in this paper draws on the general literature on learning and process improvement, the literature dedicated to pilot production, and the literature focusing directly on yield management. General learning models in manufacturing environments can be divided into two categories, *autonomous learning* and *induced learning*. Autonomous learning assumes that learning is merely a by-product of increased cumulative production volumes, and is often referred to as *learning by doing*. Autonomous learning models draw on a long history, including the early papers by Wright (1936) and Arrow (1962). Empirical support is ample and comes from a variety of different industries, including musical instruments (Baloff, 1971), semiconductors, apparel, auto assembly (Joskow and Rozanski, 1979) and nuclear power plants (Lieberman, 1984).

Induced learning models, on the other hand, view learning as a deliberate process beyond the mere accumulation of production experience to *proactively accumulate and share knowledge* (e.g. Mody, 1989, Adler, 1990, and Zangwill and Kantor, 1998). Dorroh et al. (1994) and Hatch and Mowery (1998) stress the importance of investing enough resources to facilitate knowledge acquisition and sharing. Tang (1991) discusses how inspection policies and improved information sharing drive up production yields. Dutton and Thomas (1984) and Terwiesch and Bohn (2001) emphasize the impact of experimentation on accumulating knowledge. Fine (1986), Li and Rajagopalan (1998), and Carrillo and Gaimon (2000) provide excellent reviews on how learning is induced through process changes that lead to increased long-term effective production capacity. Finally, Mody (1989), Adler (1990), Argote et al. (1990), Argote and Ingram (2000), Szulanski (2000), Darr and Kurtzberg (2000), and Lapre and Wassenhove (2001) analyze knowledge creation and sharing among production facilities with *similar* production processes. Hatch and Mowery (1998) go one step further and advocate duplication of process equipment between development and manufacturing facilities. Intel's *copy exactly* strategy, as explained in detail in McDonald (1998), is a prominent example for the importance of knowledge transfer between similar, if not identical, production lines.

Following the ample literature on autonomous learning and information sharing, Section 3 of this paper introduces a pilot production model based on autonomous learning alone. Section 4 of this paper incorporates the results from Section 3, models knowledge creation and sharing among production lines with similar production processes, and shows how process commonality affects pilot production strategies. In contrast to the extant empirical literature on knowledge creation and sharing, our model provides a descriptive analytical model that reflects our own experience in a variety of different industries as well as empirical observations (e.g. McKinsey Global Institute, 2001; Clark, 2002; Terwiesch and Xu, 2004). Moreover, our proposed model provides, to the best of our knowledge, the first analytical approach to characterizing when knowledge sharing should be desirable among production lines with common production processes.

Bohn and Terwiesch (1999), Terwiesch and Bohn (2001), and Terwiesch and Xu (2004) also discuss process improvement during pilot production. The underlying premise of their work is that experiments and deliberate process changes increase process knowledge at the cost of temporary capacity reductions. Our pilot production model in Section 3 of this paper is related to their work since it focuses on interactions among capacity utilization and process improvement during pilot production. However, it differs from Bohn and Terwiesch (1999) and Terwiesch and Bohn (2001) in two aspects. First, we model the process improvement through cumulative production experience, i.e., learning by doing rather than carrying out controlled experiments. In particular, our model emphasizes the trade-off between allocating production capacity to pilot production for a new product with low yield versus allocating production capacity to the incumbent product with high and stable yield levels. Second, our model follows a continuous time approach rather than a discrete time approach as used by the aforementioned studies.

3 Pilot Production without Knowledge Transfer: Autonomous Learning

This section introduces the basic model of yield improvement, where manufacturers learn only by doing (i.e., autonomous learning), but not by transferring knowledge between lines. Manufacturers may have several reasons not to transfer knowledge between production lines. First, knowledge transfer requires an infrastructure to do so. For example, globally dispersed companies such as ABB have hundreds of manufacturing sites, that traditionally have acted largely independent of each other. In such an environment, challenges in transferring knowledge include a lack of transparency of what individual sites are doing, regional differences in customer requirements, as well as cultural and language barriers. Second, knowledge transfer may be prohibitively expensive. For example, if it is difficult to explicitly record knowledge in a formal syntax, that is if the relevant knowledge is predominantly tacit (Nonaka, 1994), then effective knowledge transfer depends largely on exchanging work forces across production lines. However, this is typically only economical if production lines are in close proximity of each other. Third, some of the companies we worked with actively *discourage* knowledge transfer. Archer Daniels Midland (ADM) for example, fosters a wide net of independently operating sites that are in direct competition with each other. The benefits of this competition are expected to outweigh those of close cooperation without the competitive element. Fourth, production lines may simply be too different to effectively transfer knowledge between them. Many companies that operate in high wage areas have highly automated manufacturing facilities to cover a base level of their demand. Moreover, they hold additional, more labor based, and thus more flexible, capacity in low wage areas to effectively react to fluctuations in demand. In this case, the benefits of knowledge transfer are inherently limited. Finally, if only one production line is dedicated to the product, then by definition, there is no other line to share knowledge with.

Conceptually, if no knowledge is transferred between lines, then each line can be considered independently and it suffices to investigate the single line case. Therefore, this section develops a model of a manufacturer with a single line, who currently produces a product with high and stable yields, and who has a “new” product developed that is eventually supposed to replace the incumbent, "old" product. The new product would fetch price p_1 on the market, whereas the old product sells currently at price p_0^h. While yields ($y_0 \in [0,1]$) for the old product are stable and relatively high, yields $y_1(Q(t)) \in [0,1]$ for the new product will initially be low, but, through learning, will increase over time t with the accumulated production volume $Q(t)$. Consistent with the literature on learning and yield improvement (i.e. Macher and Mowery, 2003, or Yano and Lee, 1995) we assume that the yields $y_1(\cdot)$ are an increasing function of the accumulated production volume $Q(t)$.

Competition and technical advances in the market threaten the price of the old product to erode. In particular, a price drop from p_0^h to $p_0^\ell \leq p_0^h$ is expected at some uncertain time W (with pdf $f(w)$) in the future. Moreover, the old product is expected to become obsolete beyond time T_0 and production of the new product must have commenced by T_0. This timing might be a result of an upcoming trade-show, announcements by competitors, or be dictated by corporate strategy. The new product is expected to be in the market at least until time T, by which time it is expected to have reached a terminal, stable yield level $\overline{y}_1$, even if its production commences as late as $T_0 < T$.

The direct costs of producing one unit of product, whether or not it is faulty, are c_0 and c_1 for the old and new product, respectively. Consequently, the margin on the old product is $m_0^g = y_0 p_0^g - c_0$, where $g = h$ before the price drop and $g = \ell$ afterwards. Similarly, the margin on the new product, which depend on the total cumulative production $Q(t)$, are $m_{1,Q}(Q(t)) = y_{1,Q}(Q(t)) \cdot p_1 - c_1 \leq \overline{m}_1 = \overline{y}_1 p_1 - c_1$. Therefore, as long as $m_0^g > m_{1,Q}(Q(t))$, the old product generates larger profit contributions but at the cost of delayed learning about how to ramp up yields for the new product. To evaluate this trade-off, the manufacturer has to decide how to phase in the new product during time horizon $[0, T_0]$. More specifically, the manufacturer faces the principal question of what percentage $x(t) \in [0,1]$ of its capacity K to allocate to the new product at any given point in time during the time interval $[0, T_0]$. Denoting[1] the capacity allocation policy over time horizon $[0, T_0]$ by $\mathbf{x}$ and the associated profit by $\Pi(\mathbf{x})$, the manufacturer's problem can be formulated as the *Single Line Capacity Allocation Problem* (**SLCAP**) problem, where the manufacturer maximizes expected profit over period $[0, T]$:

$$\max \; E[\Pi(\mathbf{x})] = K \cdot \left[\begin{array}{c} m_0^h \cdot \int_0^{T_0} f(w) \cdot \left(\int_0^{\omega} [1 - x(t)] \; dt \right) d\omega + m_0^l \cdot \int_0^{T_0} f(w) \cdot \left(\int_w^{T_0} [1 - x(t)] \; dt \right) d\omega + \\ \int_0^{T_0} x(t) \cdot m_{1,Q}(Q(t)) \; dt + \int_{T_0}^{T} m_{1,Q}(Q(t)) \; dt \end{array} \right] \tag{1}$$

$$\text{s.t.} \;\; 0 \leq x(t) \leq 1 \;\; \forall t \in [0, T] \tag{2}$$

The first two integrands in the objective function (1) of $SLCAP$ express the profit contribution of the old product during period $[0, T_0]$ and the remaining integrands those from the new product during periods $[0, T_0]$ and $[T_0, T]$. Implied in the objective function is that both, the production allocation policy and the yield function are reasonably well behaved; in particular, that they are Riemann integrable. Not much generality is lost by the implications, as ill behaved policies are difficult, if not impossible to implement, and yield functions tend to be indeed fairly smooth. The following proposition characterizes the optimal solution and simplifies the problem structure considerably:

Proposition 1 *There is an optimal policy, such that the production of the old product stops permanently whenever a new product is introduced.*

Proof. We first will show that $x(t) \in \{0, 1\}$ at any time t. Suppose not and let $0 < \widehat{x}(\tau) < 1$ in the optimal policy $\widehat{\mathbf{x}}$. Since the policy is optimal and constraint (2) is not binding at time τ, the first derivative

[1] The Appendix provides an overview of the entire notation used in this paper.

of the objective function with respect to $\widehat{x}(\tau)$

$$\begin{aligned}\frac{\partial E[\Pi(\widehat{x})]}{\partial \widehat{x}(\tau)} &= K \cdot \left[\begin{array}{c} -m_0(\tau)\frac{\partial \int_0^{T_o} f(\omega)\left(\int_{\phi_1(\tau)}^{\phi_2(\tau)} \widehat{x}(t)dt\right)d\omega}{\partial \widehat{x}(\tau)} + \frac{\partial \int_0^{T_0} \widehat{x}(t) m_{1,Q}(\widehat{Q}(t)) \ dt}{\partial \widehat{x}(\tau)} \\ + \frac{\partial \int_{T_0}^{T} m_{1,Q}(\widehat{Q}(t)) \ dt}{\partial \widehat{x}(\tau)} \end{array}\right] \\ &= K \cdot \left[\begin{array}{c} -m_0(\tau) + m_{1,Q}(\widehat{Q}(T_0)) \ - m_{1,Q}(\widehat{Q}(\tau)) \\ + \int_\tau^{T_o} m_{1,Q}(\widehat{Q}(t)) \ dt + \int_{T_o}^{T} m'_{1,Q}(\widehat{Q}(t)) \ dt \end{array}\right] \end{aligned} \tag{3}$$

must vanish. Equivalently

$$m_0(\tau) - \left[m_{1,Q}(\widehat{Q}(T_0)) \ + \int_{T_o}^{T} m'_{1,Q}(\widehat{Q}(t)) \ dt\right] = \int_\tau^{T_o} m_{1,Q}(\widehat{Q}(t)) \ dt - m_{1,Q}(\widehat{Q}(\tau)) \tag{4}$$

obtains.

Notice that, for any given policy $\widehat{\mathbf{x}}$, the LHS in (4) is constant for all $\tau \le w$ as well as for all $\tau > w$. Let there be any interval I, such that $w \notin I$ and such that $0 < \widehat{x}(\tau) < 1$, $\forall \ \tau \in I$. Equation (4) must then hold for all $\tau \in I$, which is a contradiction because the RHS in (4) is a strictly decreasing function in $\tau \in I$. Consequently, any optimal policy can differ from 0 or 1 only at individual *points* of time, but not during any *interval*. But such a policy is of no managerial relevance, nor does it perform any better than a policy where $\widehat{x}(t) = 0$ for all such points.

Any optimal policy consists thus of N consecutively numbered and nonadjacent intervals $[s_i, t_i]$ such that $x(t) = 1$ for all $t \in [s_i, t_i]$, $i \in \{|1, N|\}$ and $x(t) = 0$ elsewhere. With $t_0 = 0$ and $t_N = T_0$ we can thus, for any given realization w of W, reformulate the objective function (1) in *SLCAP* as:

$$\Pi(\widehat{x}|w) = K \cdot \left(\begin{array}{c} \sum_{i=0}^{\widetilde{n}-1}(s_{i+1} - t_i) \cdot m_0^h + \max(0, w - t_{\widetilde{n}}) \cdot m_0^h + \max(0, s_{\widetilde{m}} - w) \cdot m_0^l \\ + \sum_{i=\widetilde{m}}^{N-1}(s_{i+1} - t_i) \cdot m_0^l \\ + \sum_{i=1}^{N} \int_{s_i}^{t_i} m_{1,Q}\left(K \cdot \sum_{j=1}^{i-1}(t_j - s_j) + K \cdot (t - s_j)\right) dt \quad + \int_{T_0}^{T} m_{1,Q}(Q(t)) \ dt \end{array}\right) \tag{5}$$

where,

$$\begin{aligned} \widetilde{n} &= \max_{n \in \{|0,N|\}} \{n \mid s_n \le w\} \\ \widetilde{m} &= \min_{n \in \{|0,N|\}} \{n \mid t_n \ge w\} \end{aligned} \tag{6}$$

It remains to show that there is an optimal policy with $N = 1$. Let $\widehat{\mathbf{x}}$ be a policy with $N = \widehat{N} > 1$ such that for some $[s, s+2\Delta) \subseteq [0, T_0]$, $\widehat{x}(t) = 1$ for all $t \in [s, s+\Delta)$ and $\widehat{x}(t) = 0$ for all $t \in [s+\Delta, s+2\Delta)$. Consider policy $\widetilde{\mathbf{x}}$ such that $\widetilde{x}(t) = \widehat{x}(t)$ for all $t \notin (s, s+2\Delta)$, $\widetilde{x}(t) = 0$ for all $t \in [s, s+\Delta)$, $\widetilde{x}(t) = 1$ for all $t \in [s+\Delta, s+2\Delta)$. Then,

$$\Pi(\widehat{x}|w) - \Pi(\widetilde{x}|w) = \left\{\begin{array}{ll} K \cdot \max(0, (s - w) \cdot (m_0^h - m_0^l), & \text{if } w \le s + \Delta \\ K \cdot \max(0, s + 2\Delta - w) \cdot (m_0^h - m_0^l) & \text{if } w \ge s + \Delta \end{array}\right. \le 0 \tag{7}$$

and policy $\widetilde{\mathbf{x}}$ with $\widetilde{N} = \widehat{N} - 1$ is at least as good as policy $\widehat{x}$ and the result obtains. Indeed, such a policy is unique if $m_o^h > m_o^\ell$. ∎

Given this result, it is no longer necessary to express the yields and margins as a function of the cumulative production volumes $Q(t)$ and we can simplify our notation to $\xi_1(t - v) = \xi_{1,Q}(K(t - v))$ where $\xi \in \{m, y\}$

and where v is the switching time from the old to the new product. Thus $SLCAP$ simplifies to **SLCAP′**:

$$E[\Pi(v)] = K \cdot \left(\int_0^{T_0} \left[m_0^h \cdot \min(w,v) + m_0^l \cdot \max(v-w,0) \right] \cdot f(w) dw + \int_v^T m_1(t-v)\, dt \right) \tag{8}$$

$$\text{s.t.} \quad 0 \le v \le T_0 \tag{9}$$

Proposition 2 *The optimal production switching time from the incumbent product to the new product is*

$$v^* = \begin{cases} 0 & \text{if } m_0^h \le \overline{m}_1, \\ w & \text{if } m_0^h > \overline{m}_1 \ge m_0^\ell, \\ T_0 & \text{if } \overline{m}_1 < m_0^\ell. \end{cases} \tag{10}$$

Proof. The first two derivatives of (8) with respect to v are simply

$$\frac{dE[\Pi(v)]}{dv} = K \cdot [m_0(v) - m_1(T-v)] \tag{11}$$

and

$$\frac{d^2E[\Pi(v)]}{dv^2} = K \cdot m_1'(T-v) \ge 0, \tag{12}$$

Thus, $E[\Pi(v)]$ is convex over both intervals $[0,w)$ and $(w,T_0]$ and $v^* \in \{0,w,T_0\}$ obtains. Further notice that, by assumption, $y_1(T-T_0) \cong \overline{y}_1$ is the final yield for the new product. Consequently, $m_1(T-v) \cong \overline{m}_1$ for all $v \le T_0$ and the proposition follows easily. ■

The implications of Propositions 1 and 2 are interesting. First, without knowledge transfer, partial production, or pilot production in our terms, of the new product is dominated by bang-bang type strategies, where all production of the incumbent product is seized, once ramp-up for the new product commences. This implies that upon production start, learning how to improve yields is paramount and should not be delayed for the sake of reaping continued high margins from the incumbent product. Second, a switch-over to the new product occurs either as soon or as late as possible or when the price of the incumbent product drops. As a consequence, myopic policies, based on the current, observable price for the incumbent product are optimal. Third, since the manufacturer reacts based on the price for the incumbent product, knowledge of its future price development, both in respect to price levels and timing of price drops, is not necessary to derive optimal strategies. Fourth, the results are very robust with respect to the assumptions. In particular, they are independent of any details on how the production process is improved as long as production yield levels are increasing as more production occurs. Indeed, it is sufficient that yields are nondecreasing in expectation, such that yield functions with random error terms due to, for example, process excursions or tool failures are covered by these results as well. Moreover, the results are also robust with respect to our definition of margins, as the results hold as long as the margins are nondecreasing over $[0,T]$. Fifth, the interpretation of the results in Proposition 2 is interesting. The incumbent product is continued for as long as its *current* margins are higher than the expected *future* margins of the new product at time T. Thus, the manufacturer only needs to be able to estimate the final yield of the product, but not the shape of the yield curve. This also implies that a myopic policy that compares *current* margins of *both products* is bound to lead to suboptimal policies and belated product introductions. While this result is contingent on our assumption that the new product reaches its terminal yield level after full production, it holds in close approximation if the yield curve is very flat after $T - T_0$ units of time of full production. Otherwise, the principal insights of Propositions 1 and 2 remain valid, but the conditions for the optimal switching times become less candid.

Finally, in complete analogy to the proofs presented here, albeit at the cost of considerable additional notation, the results can be extended to the case of an arbitrary number of random price-drops:

Corollary 3 *Let z be a random positive integer, $w_0 = 0$, $w_{z+1} = T_0$, $p_{z+1} = 0$ and let w_i be random numbers such that $w_i < w_{i+1}$, for $i = 0, 1, ..., z$. Furthermore, let the random price for the incumbent product during period (w_i, w_{i+1}) be $p_0^i > p_0^{i+1}$ for $i = 0, 1, ..., z$. Let $m_0^i = y_0 p_0^i - c_0$. The optimal production switching time from the incumbent product to the new product is*

$$v^* = \begin{cases} 0 & \text{if } m_0^0 \leq \overline{m}_1, \\ w_i & \text{if } m_0^{i-1} > \overline{m}_1 \geq m_0^i, \; i = 1, ..., z, \\ T_0 & \text{if } \overline{m}_1 < m_0^z. \end{cases} \tag{13}$$

The corollary essentially states that switch-over either occurs as early or as late as possible, or when the current profit contribution of the incumbent product drops below that of the future contributions of the new product. All implications for Proposition 2 hold for Corollary 3 in complete analogy.

We also need to emphasize that we ignored the issue of strategic competition in our analysis. Manufacturers may act strategically on how they allocate their total production capacity depending on their competitors' actions in the market. For this case, a different model is needed to determine the best capacity allocation between consecutive generations of products. In addition, we ignored any possible uncertainty in production capacity. Again, a different model is needed depending on how risk sensitive the manufacturer is. However, we conjecture that a bang-bang type of policy would still hold true for any risk-neutral manufacturer. In all these cases, the model and insights presented here can serve as natural building blocks for a more detailed discussion. Finally, we assumed that production yield levels on one production line are independent of those on other production lines. We relax this assumption in the next section where we analyze how pilot production lines are managed when there is a dependency among production yield levels through knowledge transfer among production lines.

4 Pilot Production with Knowledge Transfer

While the results of the previous section are quite general and comprehensive, they are also deeply dissatisfying. Essentially, they relegate the manufacturer to the role of a passive bystander, who just *reacts* to the development on the market; that is, the price decay of its incumbent products. *Proactive* manufacturers instead, will strive to manipulate yield curves to enable earlier market entry and thus higher profits. In particular, they will try and improve yield curves by learning more about the production process before fully committing capacity to the new product. The previous session established that it is suboptimal to do so on any *one* line. Consequently, in this section, we extend our discussion to the case where the manufacturer has $n > 1$ production lines *and* is willing and able to meaningfully transfer knowledge gained on one production line, the pilot line, to the remaining lines. Again, the preceding results warrant that, at any point in time, each manufacturing line is either fully dedicated to the incumbent product or to the new product but not to both. Using this result as a building block, we will now consider the case where the manufacturer dedicates one line to pilot production.

In this scenario, production on the pilot line commences as soon as the specifications for a manufacturable product are available, say at time 0, and continues, in complete analogy to the previous section, at least until time T, by which time it will have attained its terminal yield $\overline{y}$. At some time $\tau \in [0, T_o]$, when the yield on the pilot line is $y(\tau)$, the cumulative knowledge gained on the pilot line is utilized to help provide a "jump-start" to the remaining or receiving lines. In the ideal case, if every single bit of knowledge can be transferred, the receiving lines will immediately start with the same yield $y(\tau)$ as the pilot line. In the worst case, none of the knowledge gained on the pilot line is useful or transferable, and the receiving lines will start with the initial yield on the pilot line $y(0)$. Thus, depending on how much knowledge can be transferred, the yield level on the receiving lines is "thrown back" to an earlier yield level, say $y(\gamma\tau)$ of the pilot line, where $\gamma \in [0, 1]$. Clearly, if the processes on the lines are very dissimilar, then very little knowledge can be transferred and one should expect γ to be close to 0. Conversely, with highly similar processes, such as Intel's "copy exactly" strategy, γ can be expected to be closer to 1. We therefore refer to γ as the *process similarity index*. Terwiesch and Xu (2004) provide convincing empirical evidence for this impact of process similarity, by comparing Intel's yield curves before and after the introduction of copy exactly.

Once the receiving lines commence manufacturing, they gather their own manufacturing experience, and yields will continue to rise due to autonomous learning on the individual lines. For simplicity we assume that all receiving lines will learn at the same rate. Also, in analogy to the previous section, we again assume that the duration $T - T_o$ is long enough to attain the terminal yield level on any line. If the receiving lines have the same intrinsic ability to learn as the pilot line, then we would expect that, at a given yield level, the receiving lines and the pilot line learn at the same rate. Notice that in this case, the receiving lines will always be $(1-\gamma)\tau$ units of time "behind" the pilot line, that is, for a given τ, the yield at the receiving lines should be $y_r(t|\tau) = y(t - (\tau - \gamma\tau))$. Similarly, if the receiving lines have no intrinsic learning ability at all, then the yield will remain stagnant[2] at $y_r(t|\tau) = y(\gamma\tau)$. If the intrinsic ability is less than that of the pilot line, then one would expect that, for a given yield level, the receiving lines do not quite learn at the same rate as the pilot line. They may, however, learn at a faster rate than the current learning rate of the pilot level, since lower yield levels bear more potential for improvement. We address the different levels of intrinsic learning ability in the following yield function for the receiving lines

$$y_r(t|\tau) = y(\beta(t - \tau) + \gamma\tau). \tag{14}$$

The term $\beta \in [0, 1]$ addresses the skill level of the receiving lines. A low β implies little intrinsic skills to learn, whereas $\beta = 1$ implies that the receiving lines are as skilled as the pilot line. We therefore refer to β as the *skill similarity index*[3]. Figure 1 depicts the yield curves of the receiving lines for several values of β. Independent of β, the starting yield for the receiving lines is $y(\gamma\tau) > y(0)$, the starting yield without knowledge transfer. If the receiving lines have no ability to learn on their own ($\beta = 0$), the yield will stay flat at this level. If the receiving lines are as skilled as the pilot line, the yield curve stays horizontally parallel to the pilot line's yield curve. For any β in between, the horizontal gap becomes larger, but the vertical gap will nevertheless narrow down, as both curves converge to the final yield $\overline{y}$. Function (14) has several desirable and interesting properties. First, with $y(t)$ being concave increasing in t, $y_r(t|\tau)$ is also concave increasing in t. Interestingly, with $\frac{\partial y_r(t|\tau)}{\partial \tau} = (\gamma - \beta) \cdot y_r'(t|\tau)$ and $\frac{\partial^2 y_r(t|\tau)}{\partial \tau^2} = (\gamma - \beta)^2 \cdot y_r''(t|\tau) < 0$, $y_r(t|\tau)$ is concave *increasing* in τ if and only if $\gamma > \beta$, otherwise it is concave *decreasing*. Thus, if the skill similarity index

[2]The reader may object that this case contradicts the assumption that yields will eventually attain the final yield $\overline{y}$. This is indeed true, and this limit case is only introduced to serve intuition. It is not our intention to suggest this case as a realistic scenario or worthwhile much attention.

[3]All insights of this paper extend to the case where no upper bound is imposed on β. However, since $\beta > 1$ implies that the receiving lines learn faster than the pilot line, we restrict our attention to the case where no other line is capable to learn faster than the pilot line. Otherwise, the manufacturer would be better off by dedicating the line with faster learning capabilities as the pilot line.

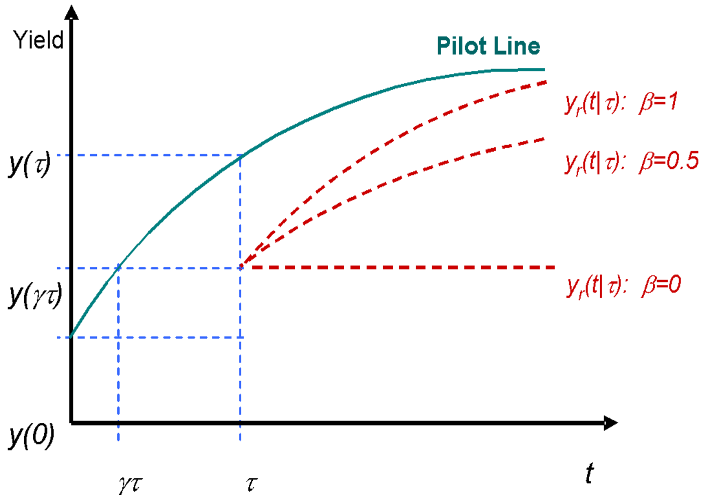

Figure 1: Yield curves on receiving lines for different parameter constellations

β exceeds the process similarity index γ, delayed product introduction will lead to a lower yield curve on the receiving lines than immediate introduction. However, as we will show shortly, this does not necessarily imply that it is optimal to immediately introduce the new product whenever $\beta > \gamma$. Conversely, if $\beta < \gamma$, then longer delays in product introduction leads to higher yield curves. Again, we will show shortly, that this does not necessarily imply introducing the new product as late as possible. Second, for $\tau = 0$, no knowledge is transferred and the lines operate in isolation of each other, much as in the previous section. Third, at time $t = \tau$, the receiving lines have not yet accumulated any knowledge on their own, and the yield level depends only on the amount of knowledge transferred from the pilot line. Fourth, additional yield improvements, after time $t = \tau$, depend solely on the intrinsic ability to learn, that is they are driven by the skill level β of the receiving lines. Finally, if the receiving lines are perfect clones of the pilot line, that is if $\gamma = \beta = 1$, then the yield levels of the receiving lines will jump to the levels of the pilot line upon knowledge transfer and all lines stay in lockstep with each other thereafter.

In complete analogy to the previous section, define margins as $m(t) = y(t) \cdot p_1 - c_1$ and $m_r(t|\tau) = y_r(t|\tau) \cdot p_1 - c_1$ on the pilot line and the receiving lines, respectively. If the manufacturer has n manufacturing lines of equal capacity $\frac{K}{n}$, then the *Multiple Line Capacity Allocation Problem* (**MLCAP**) can be defined as follows:

$$\max \quad \Pi(\tau) = \frac{K}{n} \cdot \int_0^T m(t)dt + K \cdot \frac{n-1}{n} \left(\int_0^\tau m_o(t)\,dt + \int_\tau^T m_r(t|\tau)\,dt \right) \tag{15}$$

$$s.t. \quad 0 \leq \tau \leq T_0 \tag{16}$$

Proposition 4 *Total profit $\Pi(\tau)$ is concave in the launch time τ of the new product.*

Proof. According to Leibniz's rule, the first derivative is

$$\begin{aligned} \frac{\partial \Pi(\tau)}{\partial \tau} &= K \cdot \frac{n-1}{n} \cdot \left(\begin{array}{c} m_o(\tau) + \int_\tau^T \partial \frac{y(\beta(t-\tau)+\gamma\tau)\cdot p_1 - c_1}{\partial \tau} \; dt \\ -(y(\gamma\tau) \cdot p_1 - c_1) \cdot \frac{d\tau}{d\tau} \end{array} \right) \\ &= K \cdot \frac{n-1}{n} \cdot \left(m_o(\tau) - \left[\frac{\gamma}{\beta} m_r(\tau) + \left(1 - \frac{\gamma}{\beta} \right) \cdot \overline{m} \right] \right), \end{aligned} \tag{17}$$

yielding for the second derivative

$$\frac{\partial^2 \Pi(\tau)}{\partial \tau^2} = K \cdot \frac{n-1}{n} \cdot \left(m_o'(\tau) - \frac{\gamma}{\beta} m_r'(\tau) \right) < 0.$$

■

Notice the prominent role the quotient $\frac{\gamma}{\beta}$ of the process and similarity skill indexes plays in the first derivative of the profit function. To emphasize the importance of this quotient we introduce the following definition.

Definition 1 *Define* $\rho = \frac{\gamma}{\beta}$ *as the focus index. A manufacturer is said to be* process focused *if* $\rho > 1$*,* skill focused *if* $\rho < 1$ *and* focus balanced *if* $\rho = 1$*.*

An example for a process focused manufacturer is Intel. With their copy exactly strategy, manufacturing sites are highly similar, i.e. γ is very close to the ideal of 1. Potential for autonomous learning and process improvement by line workers, once the process has been established is limited though. Consequently, skill levels will be lower on the receiving lines than on the pilot lines. ABB on the other hand features limited similarity between manufacturing sites, but has a tradition of employing highly skilled mechanics and local engineers who are expected to improve productivity and yields autonomously at individual sites. The concept of focus balanced manufacturers is of course somewhat stylized as per definition, it requires the exact equality $\gamma = \beta$. If we admit values for ρ of approximately 1, then many companies might fall in this category. Almost all modern automotive manufacturers have globally coordinated and similar processes, yet emphasize the importance for local employees to continuously help improve processes[4].

We would like to stress that the focus index is a relative and not an absolute measure. For example, compare process focused company A with $\gamma_A = 0.9$, $\beta_A = 0.6$ and $\rho_A = 1.5$ and skill focused company B with $\gamma_B = 0.25$, $\beta_A = 0.5$ and $\rho_B = 0.5$. Obviously, in absolute terms, company A emphasizes both, skills and process similarity to a larger degree than company B. However, company A puts relatively more emphasis on its process similarities, whereas company B focuses more on its skill levels than on its process similarities. The focus based characterization of manufacturers allows us to express the first order condition for $MLCAP$ as

$$m_o(\tau) = \rho m_r(\tau) + (1 - \rho) \cdot \overline{m} \tag{18}$$

and gives rise to the following corollaries.

Corollary 5 (Market Entry Timing) *: It is optimal to enter the market*

(a) immediately, at time $\tau = 0$*, if* $\rho \leq \frac{\overline{m} - m_o(0)}{\overline{m} - m_r(0)}$*,*

(b) late, at time $\tau = T_0$*, if* $\rho \geq \frac{\overline{m} - m_o(T_o)}{\overline{m} - m_r(T_0)}$*,*

(c) and otherwise at time τ *such that the margins for the old product are equal to the weighted average of initial (receiving line) margins* $m_r(\tau)$ *and terminal margins* $\overline{m}$*. The weights are the focus index* ρ *and* $1 - \rho$*, respectively.*

Proof. The proof is trivial as the concavity of the objective function requires for optimality that the first order condition (18) holds or that constraint (16) is binding. In (a) the first derivative of the objective

[4] Being focus balanced in our definition can of course also be a euphemism for lack of focus on both skills and processes, as low scores on both can also yield a quotient close to 1.

function is strictly negative, and constraint (16) is binding at $\tau = 0$. Similarly, in (b) the first derivative of the objective function is strictly positive, and constraint (16) is binding at $\tau = T_0$. Finally, (c) is simply a verbal equivalent of the first order condition (18). ■

Table 1: Market Entry Timing

$\tau = 0$	$\tau = T_0$	$0 < \tau < T_0$
$\rho \leq \frac{\overline{m}-m_o(0)}{\overline{m}-m_r(0)}$	$\rho \geq \frac{\overline{m}-m_o(T_o)}{\overline{m}-m_r(T_0)}$	$m_o(\tau) = \rho m_r(\tau) + (1-\rho) \cdot \overline{m}$

The result is quite distinct from that in Section 3. There, the market entry decision was based on a comparison of the current margins from the incumbent product and the terminal margins from the new product. Here, the initial margins for the new product are also drawn into this comparison as shown in Table 1. Initial margins gain relatively more importance for process focused manufacturers, whereas terminal margins are of higher importance for skill focused manufacturers. The latter are more likely to enter the market at $\tau = 0$, since a lower ρ makes it more likely that condition (a) of the corollary is satisfied. However, being skill focused is neither a necessary nor a sufficient condition for immediate entry, as $\frac{\overline{m}-m_o(0)}{\overline{m}-m_r(0)}$ is not limited to a particular range of values. Only for $m_o(0) > m_r(0)$ is being skill focused indeed a necessary condition. Similarly, process focused manufacturers are more likely to enter the market as late as possible, but again being process focused is neither a necessary nor a sufficient condition for market entry at time T_0. It becomes a necessary condition only if $m_r(T_0) > m_o(T_0)$. All other things equal, skill focused manufacturers will thus tend to enter the market earlier than process focused manufacturers. It is interesting to observe in this context, that AMD, after playing catch-up with Intel in the late 1990s (McKinsey Global Institute, 2001), is now generally considered as being quicker to market than its much more process focused competitor Intel. It would be overstating our results to argue that the relative skill focus of AMD is the reason for AMD lately beating Intel to the market. However, we do argue that, if AMD's corporate strategy aims at being first to market, then its skill focused manufacturing strategy is perfectly aligned with this overall corporate strategy. Finally, it is noteworthy that market entry is independent of the absolute levels of β and γ , that is of the ability to learn and to disseminate knowledge. Instead, it is exclusively based on the ratio between them, that is on a firm's relative focus on process or skills. The insights from Corollary 5 are highlighted in Table 2.

Corollary 6 (Focus Balanced Manufacturers) *: For focus balanced manufacturers it is optimal to enter the market*

Table 2: Process Focused vs Skill Focused Manufacturers

	Initial Margins	Terminal Margins	Market Entry
Process Focused	More Important	Less Important	More Likely at $\tau = T_0$
Skill Focused	Less Important	More Important	More Likely at $\tau = 0$

Table 3: Focus Balanced Manufacturers

Knowledge Transfer	No Knowledge Transfer
Initial Margins ↓ Market Entry Time	Terminal Margins ↓ Market Entry Time

(a) *immediately, at time* $\tau = 0$, *if* $m_r(0) \geq m_o(0)$,

(b) *late, at time* $\tau = T_0$, *if* $m_r(T_0) \leq m_o(T_0)$,

(c) *and otherwise at time* τ *such that the margins for the new product on the receiving lines,* $m_r(\tau)$, *are equal to the margins for the old product* $m_o(\tau)$.

(d) *In the latter case, the margins from the old product at time* τ *must be equal to the margins from the new product manufactured on the pilot line at (earlier) time* $\gamma\tau$.

Proof. The proofs for (a) to (c) are simply the special cases of Corollary 5 with $\rho = 1$. With the result in (c), the result in (d) follows immediately from the definition of the yield in equation (14). ■

For any nontrivial, interior solution, it is thus optimal for focus balanced manufacturers to enter the market whenever initial margins (on the receiving lines) are equal to the current margins of the incumbent product. Notice that this result is in stark contrast to the result in Section 3. There, without knowledge transfer, the optimal market entry time depends exclusively on the *terminal* margins. Here, the optimal market entry time depends exclusively on the *initial* margins. We summarize this result in Table 3. Clearly then, all others equal, knowledge transfer can lead to a much earlier market entry. For all, but the stylized case with $\gamma = 1$, (b) implies that the margins from the pilot line will be larger than the margins for the old product before the new product is introduced on all lines. Consequently, switching to the new product when margins from the pilot line approach those of the incumbent product is suboptimal.

Corollary 7 (Skill Focused Manufacturers) *:*

(a) *If it is not optimal to enter the market immediately, then it is optimal for a skill focused manufacturer to enter the market* ***before*** *initial margins for the new product have reached the margins by the old product, that is at a time* τ *such that* $m_r(\tau) < m_o(\tau)$.

(b) *Manufacturers with no focus at all on process similarity between lines* (*i.e.* $\gamma = \rho = 0$), *will enter the market*

  (1) *immediately, at time* $\tau = 0$, *if* $\overline{m} \geq m_o(0)$,

  (2) *late, at time* $\tau = T_0$, *if* $\overline{m} \leq m_o(T_0)$,

  (3) *and otherwise as soon as the margins of the incumbent product drop to the level of the terminal margins of the new one product, that is once* $m_o(\tau) = \overline{m}$ *obtains.*

Proof. (a) is the special case of Corollary 5 with $\rho < 1$ and (b) is the special case with $\rho = 0$. ■

Skill focused manufacturers thus do not wait to enter the market until the initial margins reach the margins of the incumbent product. Instead, they sacrifice some of the profit from the incumbent product, for the sake of faster yield ramp-up on the receiving lines. Fundamental driver is that skill focused manufacturers ultimately learn faster autonomously, than by knowledge transfer. Essentially, they face the trade-off of going too early to market, and sacrificing profit contributions from the incumbent product, versus going too late to market and not benefiting enough from the knowledge transfer from the pilot line, at least relative to their autonomous learning skills. In the extreme case, where no knowledge can be transferred ($\gamma = 0$), the market entry conditions are identical to the results of Section 3, since this is the simple case of n independent lines.

Corollary 8 (Process Focused Manufacturers) *:*

*(a) If it is not optimal to enter the market late, that is at time $\tau = T_0$, then it is optimal for a process focused manufacturer to enter the market **after** initial margins for the new product have reached the margins by the old product, that is at a time τ such that $m_r(\tau) > m_o(\tau)$.*

(b) Manufacturers with no autonomous learning skills (i.e. $\beta = 0$), will enter the market

(1) late at time $\tau = T_0$, if $m_r(T_0) < \overline{m}$,

(2) or otherwise at the earliest time τ, such that $m_r(\tau) = \overline{m}$.

Proof. (a) is the special case of Corollary 5 with $\rho > 1$. To see that (b) is true notice that the limit of the first derivative (17) as β approaches 0 is

$$\underset{\beta\to 0}{Lim}\frac{\partial \Pi(\tau)}{\partial \tau} = \begin{cases} K \cdot \frac{n-1}{n} \underset{\beta\to 0}{Lim}\left(\left(\frac{\gamma}{\beta}\left[\overline{m} - m_r(\tau)\right]\right)\right) > 0 & \text{if } \overline{m} > m_r(\tau) \\ K \cdot \frac{n-1}{n} \cdot \left(m_o(\tau) - \overline{m}\right) > 0 & \text{if } \overline{m} < m_o(\tau) \\ K \cdot \frac{n-1}{n} \cdot \left(m_o(\tau) - \overline{m}\right) < 0 & \text{if } \overline{m} > m_o(\tau) \end{cases} \tag{19}$$

■

Part (a) of the corollary is quite remarkable as it shows that process focused manufacturers should postpone switch-over even beyond the point where the new product would catch already higher margins than the incumbent. The reason of course is that even more pilot line learning will be utilized by further postponement. Process focused manufacturers thus need to develop the discipline to avoid myopic decisions based on currently observed margins, and instead focus on reaping future benefits from continued pilot line experimentation.

In the extreme case of no autonomous learning skills at all ($\beta = 0$), transferring as much knowledge as possible from the pilot line is optimal. Consequently, knowledge transfer happens only "by force" (at time T_o) or when the pilot line has exhausted its own potential for learning, that is when $m_r(\tau) = \overline{m}$.

The next corollary shows how the optimal time to start full production, that is the switch-over time, is impacted by the parameters, thus providing guidelines for system design and process reengineering.

Corollary 9 (System Parameters) *: The optimal switch-over time τ^**

(a) decreases with the skill similarity index β, total capacity K, and the relative size of the pilot line $\frac{1}{n}$.

(b) increases with the process similarity index γ, if $\tau^* < \frac{\overline{m} - m(\tau^*)}{m'(\tau^*)}$

(c) decreases with the process similarity index γ, if $\tau^* > \frac{\overline{m} - m(\tau^*)}{m'(\tau^*)}$

(d) decreases with the final margins $\overline{m}$ for skill focused manufacturers

(e) increases with the final margins $\overline{m}$ for process focused manufacturers

Proof. The proof of the corollary is based on the optimality condition for the optimal launch time

$$F(\zeta,\tau^*(\zeta)) = K\cdot\frac{n-1}{n}\left\{m_o\left(\tau^*\right)-\left[\left(1-\rho\right)\overline{m}+\rho m\left(\tau^*\right)\right]\right\}=0$$

where ζ is the parameter of concern. Using the implicit function theorem, we obtain

$$\frac{\partial\tau^*}{\partial\zeta} = -\frac{\frac{\partial F}{\partial\zeta}}{\frac{\partial F}{\partial\tau^*}} = -\frac{\partial\frac{K\cdot\frac{n-1}{n}\{m_o(\tau^*)-[(1-\rho)\overline{m}+\rho(m(\tau^*))]\}}{\partial\zeta}}{K\cdot\frac{n-1}{n}\cdot\left(m_o'\left(\tau^*\right)-\rho m'\left(\tau^*\right)\right)}$$

yielding for $\zeta=\beta$

$$\frac{\partial\tau^*}{\partial\beta} = \rho\frac{\overline{m}-m\left(\tau^*\right)}{\beta m_o'\left(\tau^*\right)-\gamma m'\left(\tau^*\right)}<0$$

as $m_o'\left(\tau^*\right)<0$ and $m'\left(\tau^*\right)>0$. Similarly, for $\zeta=K$ one obtains

$$\frac{\partial\tau^*}{\partial K} = \rho\cdot\frac{\tau^*}{n}\cdot\frac{m'\left(\tau^*\right)}{m_o'\left(\tau^*\right)-\rho m'\left(\tau^*\right)}<0$$

and for $\zeta=n$ one obtains

$$\frac{\partial\tau^*}{\partial n} = -\rho\cdot\frac{\tau^* K}{n^2}\cdot\frac{m'\left(\tau^*\right)}{m_o'\left(\tau^*\right)-\rho m'\left(\tau^*\right)}>0$$

which proves (a). $\zeta=\gamma$ yields

$$\frac{\partial\tau^*}{\partial\gamma} = \frac{-\overline{m}+m\left(\tau^*\right)+\tau^*\cdot m'\left(\tau^*\right)}{\beta m_o'\left(\tau^*\right)-\gamma m'\left(\tau^*\right)}$$

and (b) and (c) follow. Finally, $\zeta=\overline{m}$ yields

$$\frac{\partial\tau^*}{\partial\overline{m}} = \frac{1-\rho}{m_o'\left(\tau^*\right)-\rho m'\left(\tau^*\right)}$$

and (d) and (e) follow. ■

Corollary 9 provides guidelines for manufacturers initiating internal or responding to external system changes. If, as often is the case, competitive pressures make earlier market entry lucrative, then investment in autonomous learning skills at the receiving lines, relatively larger pilot lines or a general increase in capacity, are all aligned with the goal of reducing optimal switching time. However, increased final margins[5] will reduce optimal switching times only for skill focused manufacturers, whereas they have the opposite effect on process focused manufacturers. Finally, investments into more similar production lines do not necessarily lead to earlier switch-over. Here the direction of change is highly specific and situation dependent so that under the conditions in (b) later market entry could be the result of investments in process similarity. We summarize these results in Table 4. Insights from the corollary can thus prevent firms from investing in improvements that are not aligned with their overall market entry strategy.

5 Conclusion

We present two descriptive models to guide manufacturers through pilot production when initial yield levels are low. We first analyze how much capacity to allocate to experimental production. To that end, we

[5] In the context of this discussion, it is irrelevant if higher margins are a result of external market forces such as higher prices or lower material costs, or of internal improvements such as technological leaps.

Table 4: Impact of System Parameters on the Optimal Switch-over Time

	Skill Similarity Index	Total Capacity	Relative Size of the Pilot Line
τ^*	$\searrow$	$\searrow$	$\searrow$

	Process Similarity Index
$\tau^* < \frac{\overline{m} - m(\tau^*)}{m'(\tau^*)}$	$\nearrow$
$\tau^* > \frac{\overline{m} - m(\tau^*)}{m'(\tau^*)}$	$\searrow$

	Final Margins (Skill Focused Manufacturers)	Final Margins (Process Focused Manufacturers)
τ^*	$\searrow$	$\nearrow$

introduce an optimization model that maximizes profits for a manufacturer with only a single line - the single line capacity allocation problem ($SLCAP$). Our analysis of this problem shows that autonomous learning in isolation can never justify pilot production[6]. Indeed, with autonomous learning alone, either all production is dedicated to the incumbent or the new product, but not to both concurrently. Moreover, simple myopic policies, based on current margins of the products, are sufficient to warrant optimal results. Because only current margins are relevant for the decision to switch to the new product, the information requirements for optimal product introduction are minimal.

To the best of our knowledge, previous literature on experimental production has not considered the issue of capacity allocation explicitly. Our model therefore supplements the extant literature by explicitly modeling the capacity trade-off between two consecutive generations of products to develop experimental production strategies.

Furthermore, we model production yield levels as a function of cumulative production experience. Specifically, we treat production yield levels as an increasing function of the cumulative production quantity. Production experience models developed in the extant literature assume that unit costs of production decrease with more production experience. We can easily develop a corresponding one-to-one mapping between unit production cost and production yield levels. This mapping is quite useful since we can characterize process improvement not only through reductions in unit production cost, but also through improvement in production yield levels. Hence, our production yield model generalizes the previously developed yield models in the literature.

Finally, our assumptions regarding yield curves are quite general, imposing little limitation on the applicability of our model. However, the assumption of a single manufacturing line, or equivalently of n manufacturing lines without any interaction, limits applicability to only a subset of manufacturers. As a

[6] We must point out here that our model assumes no idle capacity, that is capacity does not exceed demand. Clearly, if there is idle capacity (for the incumbent product) then this idle capacity can be employed to accelerate learning (and increase total cumulative production volume of the new product). However, our results imply directly that no more than the idle capacity is dedicated to pilot production.

remedy, and to generate further insights, we introduce the multiple line capacity allocation model ($MCLAP$) in Section 4. In this model, two principal modes of learning are considered, learning by doing or autonomous, line specific learning, and learning through knowledge exchange between a pilot line and receiving lines. We introduce the concepts of and distinguish between process focused manufacturers, who focus on a high degree of similarity between manufacturing lines, and skill focused manufacturers who emphasize the autonomous learning skills of employees on the receiving lines.

Our first result indicates that myopic policies no longer warrant optimal decisions and the optimal switch-over time depends on the manufacturer's focus and both, current *and* future margins of the product. In particular, skill focused manufacturers should switch to full production *before* margins for the new product have caught up with those for the old product, whereas process focused manufacturers should do so only when margins from the new product are already higher than those for the old product. Thus, all other things equal, skill focus should lead to earlier product introduction than process focus. Comparing recent product introductions by AMD, who tends to be more skill focused, with those by Intel, who is perhaps the classic process focused manufacturer, seem to support these results.

Finally, investments in additional capacity, larger pilot lines or higher skill levels all lead to earlier product introduction. Higher product margins on the other hand delay product introductions for process focused firms, but accelerate them for skill focused ones. Investments in more process similarity may or may not lead to accelerated product introduction, and is highly dependent on the individual circumstances.

In conclusion, we would like to point out some possible limitations and pitfalls to the approaches presented here. First, our model in Section 4 assumes exactly one knowledge exchange between the pilot line and the receiving lines. In our experience, this assumption seems to be justified for many manufacturers, primarily because of high costs associated with knowledge transfers. Intel for example, will usually employ its pilot line to generate a comprehensive set of guidelines and productions specifications followed by training sessions for the new procedure that typically involve sending out hundreds of Intel employees to remote sites (Clark, 2002). Only in exceptional cases, such as some unexpected improvements or continued yield problems, will additional knowledge transfers take place. Bruce Sohn, the co-manager of the Rio Rancho plant of Intel, provides one such example of an additional knowledge exchange: "...identical tools in two factories of Intel kept producing different defect rates. By swapping the workers who maintained the tool, Intel learned that one group was cleaning the tool by wiping a towel in a circular motion; the other wiped back and forth..." (Clark, 2002). The example illustrates both the subtleties and costliness of knowledge transfer processes and why knowledge transfers are often limited to only one transfer. But even if the knowledge transfers themselves are not too expensive, other considerations may still reasonably limit the number of knowledge transfers to only one. For example, in much of the chemical industry changes to the process setup are prohibitively expensive, even if knowledge could easily be transferred between sites. In the pharmaceutical industry almost any change to existing processes needs renewed FDA approval which can be costly and lengthy. Because of the high costs of process changes, in these scenarios knowledge transfers from pilot lines are thus often limited to only one exchange.

However, if multiple knowledge transfers are indeed lucrative, then our model is no longer sufficient. In this case, it would be interesting to determine timing and frequency of these transfers (Loch and Terwiesch, 1998 and Yassine et al., 2008). A second related limitation is that yields are considered deterministic. While, within the framework of our model, our results should easily extend to expected yield functions for risk neutral manufacturers, allowing for (multiple) knowledge transfers between any two lines might change some of our results. In particular, multiple pilot lines might take advantage of natural fluctuations between pilot lines and only the best line would transfer knowledge to the receiving lines. Similarly, even during full production, knowledge transfer between lines could continue to be beneficial to take advantage of random learning on individual lines. While such a discussion is beyond the scope of this paper, they are worthy topics for future research.

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6 Appendix - Overview of Notation

p_1	= unit price of the new product on the market
p_0^h	= unit price of the old product before price drop
p_0^l	= unit price of the old product after price drop
y_0	= stable and relatively high yields for the old product
$y_1(Q(t))$	= yields for the new product at time t, $y_1(Q(t)) \in [0,1]$
$Q(t)$	= accumulated production volume during $[0,t]$
W	= random time with pdf $f(w)$ at which the price of the old product drops
T_0	= production end-time of the old product
T	= dedicated time for the new product, $T_0 < T$
$\overline{y}_1$	= terminal, stable yield level for the new product
c_0	= direct cost of producing one unit of the old product
c_1	= direct cost of producing one unit of the new product
m_0^g	= profit margin on the old product, where $g = h$ before the price drop; $g = \ell$ afterwards
$m_{1,Q}(Q(t))$	= profit margin on the new product at time t
$x(t)$	= percentage of capacity allocated to the new product at time t, $x(t) \in [0,1]$
K	= total production capacity per unit time
$\mathbf{x}$	= production allocation policy over time horizon $[0,T_0]$
$\Pi(\mathbf{x})$	= manufacturer's profit associated with production policy $\mathbf{x}$
v	= production switching time from the old to the new product
$\xi_1(t-v)$	$= \xi_{1,Q}(K(t-v))$, where $\xi \in \{m,y\}$
$\Pi(v)$	= manufacturer's profit associated with production switching time v
v^*	= optimal production switching time from the old to the new product
$\overline{m}_1$	$\cong m_1(T-v)$, stable, terminal profit margin of the new product
$y(t)$	= the yield level on the pilot line at time t
$\overline{y}$	= terminal yield level on the pilot line
τ	= the time at which knowledge is transferred from the pilot line
τ^*	= optimal time to start full production, the optimal switch-over time
γ	= process similarity index, $\gamma \in [0,1]$
β	= skill similarity index, $\beta \in [0,1]$
$y_r(t\|\tau)$	$= y(\beta(t-\tau)+\gamma\tau)$, the yield at the receiving lines at time t
$m(t)$	$= y(t)p_1 - c_1$, profit margin on the pilot line at time t
$m_r(t\|\tau)$	$= y_r(t\|\tau)p_1 - c_1$, profit margin on the receiving lines at time t
$m_r(t)$	= profit margin on the receiving lines at time t
n	= total number of manufacturing lines
$m_0(t)$	= profit margin on manufacturing lines from the old product at time t
$\Pi(\tau)$	= manufacturer's profit associated with knowledge transfer time τ
ρ	$= \frac{\gamma}{\beta}$, focus index
$\overline{m}$	= terminal profit margin of the new product

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