Market Preferences and Process Selection: The Value of Perfect Flexibility

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Abstract

In this paper we investigate the selection of process technologies under conditions of stochastic market preferences. We assume that the market evolves over time through *m* states or scenarios defined by the preferences of the market. In response to this evolving marketplace, a producer can respond by switching its facilities to one of *t* technological states defined by plant capabilities. We model the evolution of market preferences and policies for process selection as a Markov Decision Process and find optimal process adoption policies. In addition to optimal strategies, we define two alternative adoption strategies. "Perfect flexibility" is defined as the increase in profit that can be obtained by instantly matching process technologies to changes in market preferences, compared to a "robust" policy of selecting and employing only a single process technology.

With an objective of profit maximization, we show that when the cost of switching production processes is very high, the optimal policy is to select a single robust process and to never switch from it. In contrast, when process-switching costs are zero we show that the optimal policy is perfect flexibility where production processes are immediately matched to market preferences. An optimal production policy provably exists between these two extreme policies. We define the expected value of perfect flexibility as the difference in expected profits between a perfectly flexible policy and a robust policy. The expected value of perfect flexibility provides an upper bound to the benefit of process switching and product flexibility when market preferences are uncertain. Several numerical examples illustrate our findings.

Introduction

A common and significant problem in business management is anticipating the changing needs and preferences of customers and matching internal processes to those customer preferences. If a business ignores (or does not recognize) changing customer preferences, it runs the risk of reduced revenues due to reduced market share and of increased production costs due to a growing mismatch between production capabilities and market preferences.

There are many situations where increased process flexibility is desirable. The recent growth of the Internet and e-business has escalated the need to provide customers unprecedented levels of product personalization. The use of online consumer profiles and offline demographic factors presents the opportunity for enhanced "suggestive selling" and mass customization – if the appropriate technology and resources are in place (Hesler 1999). Even traditionally conservative mass producers like GM and Ford cannot escape the increasing emphasis on greater production flexibility. GM is moving from a "make-and-sell" to a "sense-and-respond" approach that was pioneered at its Saturn division (Sweat 1999). Further, GM now wants to move to an "anticipate-and-lead" model, using customer feedback to develop car designs, then build and deliver them to order. Indeed, the proliferation of consumer products is growing. Since the 1970's, the number of new auto models has increased from 140 to 260, the number of soft drinks from 20 to more than 87, and the number of over-the-counter pain relievers from 17 to 141 (Cox and Alm 1999). It is today's production technology that allows such a great increase in product proliferation at low costs -– at least for some industries, including computer assembly (*e.g.*, Dell Computer) and apparel manufacturing (*e.g.*, InterActive Custom Clothes and Digitoe). Changing customer demands and the desire for increased product variety draws firms to acquire more flexible production capacity.

In other situations, excessive flexibility may be a detriment. A well-known example of the potential consequences of a mismatch between customer preferences and market capabilities is the U.S. machine tool industry in the 1970's and early 1980's (Dertouzos *et al.* 1989). During this period, U.S. machine tool manufacturers believed that their customers would continue to prefer machine tools that were highly customized for individual users. Acting on this belief, manufacturers continued to organize their production processes to produce low volumes of specialized machine tools. The costs of U.S. manufacturers were necessarily high, and lead times were long since every machine was virtually a unique product. During this period, Japanese machine tool manufacturers entered the U.S. market with more standardized and less elaborate machine tools. Anticipating (and driving) customer preferences for simpler machine tools, the

Japanese were able to offer quality equipment at prices and with lead-times that were far superior to those of U.S. manufacturers. The Japanese quickly grabbed market share and profits in the machine tool industry, causing U.S. manufactures to spend the next decade scrambling to regain lost ground in the machine tool marketplace.

In this paper we investigate the selection of process technologies when market preferences change over time. We model the resulting Market Preference and Process Selection (MAPPS) problem as a Markov Decision Process (MDP) that can be solved using backward recursion techniques from dynamic programming. This provides an analytic business tool that managers can use to explore alternative policies for adapting to changing market preferences. We introduce the concept of *perfect flexibility* and the related *expected value of perfect flexibility*. We also define a *robust policy* of process selection where a single production technology is chosen for use with all possible market preferences. We show that perfect flexibility provides an upper bound for profitability in MAPPS problems, while robust policies form a lower bound. The results of several simulation studies demonstrate how these concepts can be used in practice. We conclude with a summary of our results and a discussion of future research.

Prior Research

To place this paper's contribution into perspective, we provide a brief review of the literature addressing the economic justification of process selection and capacity expansion. Our research focuses on the interaction of changing marketplace demand for product and the acquisition of advanced process technology – research on this area of interaction is recent and sparse (Li and Tirupati 1997).

Two notable early studies on technological adoption are Balcer and Lippman (1984) and Gaimon (1985a, 1985b). Balcer and Lippman developed a comprehensive dynamic, stochastic model to investigate the problem where a firm must choose between upgrading to current technology and doing nothing. They measured technological improvement solely by a reduction in production costs and showed that a firm may choose to adopt a previously available technology under certain circumstances. Gaimon's papers used deterministic control models for the acquisition of automated processes, and showed that it is rarely optimal to increase automation without at the same time modifying the level of manual output. Her work provides a methodology to identify the optimal mix of automation and labor to enhance workforce productivity. In later work, Gaimon and Ho (1994) used a dynamic game theoretic approach to examine factors that impact a firm's decision to acquire new capacity, including the effect of technology innovation on the cost of capacity.

The optimality of a "wait and see" decision-making strategy was observed by Monahan and Smunt (1989), who found that delayed acquisition of new process technology can be optimal given uncertainty in technology forecasts and potential interest rate (cost of capital) changes. They explicitly modeled the potential for reduced inventory and production costs when adopting new technology, and also allowed for scale economies. Monahan and Smunt did not, however, address capacity expansion or the potential for product-mix changes over time. Rajagopalan (1999) extended Monahan and Smunt with a model that examined the impact of uncertainty and output expansion on the adoption of a newer vintage technology. He also found that a firm might adopt a wait-and-see strategy and delay introduction of a new process technology even though demand is increasing. This delay especially occurs when the introduction of better technology imminent, but current technology is incompatible with the next generation. Li and Tirupati (1997) developed both static and dynamic "allocation" models to determine capacity strategies. Specifically, they considered two types of facilities: one where production facilities were dedicated to specific products and the other that was capable of producing all products. Their model determined the optimal mix of these two facility types with the objective of minimizing total investment costs.

Much of the literature addressing process selection can trace its roots to the related problem of capacity expansion. The classic capacity expansion paper of Manne (1961) used both deterministic and probabilistic models to determine the optimal timing and amount of increased capacity. A key conclusion developed by Manne was the observation that optimal capacity expansion increments increase as demand variance increases. In contrast to capacity expansion, a recent study by Rajagopalan, Singh, and Morton (1998) showed that variance in the evolution of a process technology can impede process adoption, *i.e.* that the acquisition of new technologies slows when there is increased uncertainty about the pace of technological evolution. Finally, as indicated by Rajagopalan and Soteriou (1994), there are many papers in the machine replacement literature (*e.g*., Pierskalla and Voelker 1976 and Chand and Sethi 1982). This stream of research does not address scale economies or growth in demand, nor does it address changes in the product-mix over time.

Extant research demonstrates that there are many competing factors that determine the optimal timing for acquiring, expanding, and replacing new process technologies. The implication for management is that the acquisition of process technologies is a complex problem that requires a close examination of the uncertainties, costs, and subsequent tradeoffs involved. Largely missing from the literature is consideration of the interaction between technology acquisition decisions and the demands of the marketplace (Li and Tirupati 1997). In this paper, we begin to address process/market interaction by investigating process selection in an environment where marketplace product preferences evolve stochastically. The resulting Market Preference and Process Selection problem provides important measures and insights into the value of process flexibility under conditions of market uncertainty.

The MAPPS Model

The Market Preference and Process Selection (MAPPS) problem is that of selecting a sequence of profit maximizing process technologies over time to satisfy evolving market preferences. This is a ubiquitous problem faced by managers in most industries serving most markets. As markets evolve and as market preferences change, managers must adopt new and alternative process technologies to meet market requirements. The MAPPS problem would be difficult enough if market preferences could be accurately predicted for some time into the future. But market preferences frequently change in unexpected, capricious, and sometime fickle ways (Fisher *et al.* 1994). The stochastic nature of market preference creates an added layer of complexity to the MAPPS problem.

Our purpose in modeling the MAPPS problem is to demonstrate an effective means of responding to stochastic changes in market preferences and to investigate the value of process flexibility – the assumptions of our model reflect this goal. First, we assume that there exists a finite number of market preference states or scenarios that the marketplace can adopt over the planning horizon of interest. Changes in market preferences are assumed to be stochastic between periods and follow a Markov process. Second, we assume that there exist a finite set of available process technologies that can be acquired and implemented at some cost to address the changing preferences of the marketplace. We model the technology choice set as static since our objective is to examine process selection and the value of flexibility and not to address technological innovation. Finally, we assume that market demand levels are fixed and unchanging. Consequently, process capacity requirements are unchanging as well. In follow-on research we apply our model to decision environments where demand levels are uncertain and where technological innovation can occur.

The state of the MAPPS system is thus determined by two factors: the state of the market and the process technology that is currently employed. Profitability in the current period depends on the interaction of these two factors. For some combinations of technology and market preference, production costs may be high (low) and revenues low (high) due to a mismatch (match) between the capabilities of current processes and market preferences. In the automotive industry for example, if current production processes are geared for the manufacture of large luxury sport utility vehicles and the market evolves to a preference for smaller economy cars, automotive production costs are likely to become relatively large, revenues relatively small, and profits potentially nonexistent.

The decision confronting a manager in a MAPPS environment is to select a sequence of process technologies that maximize profits by minimizing production costs and maximizing market revenues given uncertain future market preferences. Of related interest to the manager will be the benefits and costs of flexibly adapting to changing marketing preferences. At one extreme, managers may be under pressure to immediately respond to the preferences of the marketplace in order to meet customer demand and to maximize revenues. At the other, the manager may experience pressure to minimize technology acquisition costs by selecting a single process technology and not changing from it regardless of market preferences. It will be useful to the manager to understand the upside benefits of process flexibility and the downside costs of process inflexibility.

Market and Technology Scenarios

Modeling market structure and technological options as sets of alternative scenarios is common and intuitive. For example, in everyday language we often speak of a future market state as "up," "down," or "unchanged" without precisely defining the meaning of these terms. The specification of market states is also common in the academic literature. Hayes and Wheelwright (1979a, 1979b) dichotomize market product preferences into four scenarios (one of a kind, low standardization, high standardization, and commodities) and processes into four technological options (job shops, batch production, assembly lines, and continuous flow lines). While product preferences and process options as defined by Hayes and Wheelwright arguably exist on a continuum, the Hayes and Wheelwright "product-process matrix" has been extraordinarily useful and enduring. Further, the human tendency to solve complex problems by aggregating extensive information into a small number of discrete "chunks" and schema has been repeatedly demonstrated in the literature of problem solving and cognitive psychology (Newell and Simon 1972).

Market Structure

We posit that a finite possibility set of discrete market scenarios or states $\mathbf{M}=\{1,\ldots,M\}$ exists for planning horizon $\mathbf{H}=\{0,\ldots,H\}$, where $h=0$ is the current period prior to the acquisition of technology. Market scenario $m \in \mathbf{M}$ is defined by pertinent market variables such as product type, product mix, and demand levels. The number of possible market states and their defining variables will be highly dependent on the specific characteristics of the market under study, as our later example illustrates. Since the evolution of markets is stochastic, we model market change as an $M \times M$ transition matrix $\mathbf{\Phi}$. Element $\varphi_{ij} \in \mathbf{\Phi}$ represents the probability that the market will evolve to state j in the next period given that it is in state i in the current period. The structure of this transition matrix will determine the manner in which a market evolves over time. Markov transition matrices can be constructed to model a broad range of market evolution patterns including growing markets, declining markets, stagnant markets, and indeed can model the entire life-cycle of a product.

Structure of Process Technology

We assume that a finite possibility set of technological options $\mathbf{T}=\{1,\ldots,T\}$ exists for planning horizon $\mathbf{H}$. Technological option $t \in \mathbf{T}$ is defined by equipment descriptions, process capabilities, tolerances achieved, and other important technological variables. As with market scenarios, the set of appropriate technology options will be highly dependent on the characteristics of the problem under consideration. For the purposes of this paper, we assume that all technological options $t \in \mathbf{T}$ are immediately available, unchanging, and can be acquired and implemented at some cost.

Economic Structure

We next turn to the economic structure of the MAPPS problem and identify relevant revenues and costs, and from them, profit.

Revenues. Single period operating revenues R will be a function of both the current state of the market m and the current state of technology t within the firm. We thus model revenues as an $M \times T$ matrix $\mathbf{R}$ where element r_{mt} represents expected period revenues when the market is in state m and technology is in state t. There may well exist situations where $r_{mt} = -\infty$, representing market-technology combinations that are either technologically infeasible or untenable; *i.e.*, situations where the firm will incur unacceptable costs if it attempts to service market m using technology t.

Production Costs. Period production costs will be a function of the both the current market scenario m and current technology t. Production costs are represented as an $M \times T$ matrix $\mathbf{K}$

where element k_{mt} represents expected period production costs when the market is in state *m* and technology is in state *t.*

Technology Adoption Cost. The elements $c_{tt'}$ of matrix **C** represent the aggregate costs of switching from technological state *t* to state *t'*. Switching costs can include disposal expenses (or salvage income) from the old technology, and purchase, installation, training, and downtime expenses related to the new technology. In circumstances where a technology does not change between periods ($t'=t$), costs $c_{tt} \geq 0$ represent the period costs of maintaining the technology and servicing debt acquired to purchase the technology.

Single Period Profit. For a period in which markets are in state *m*, technology is currently in state *t* and will be switched to state *t'* in the following period, single period operating profit π is

$$\pi_{mtt'} = r_{mt} - k_{mt} - c_{tt'}.$$

Dynamic Programming Solution

In any period *h* of the planning horizon **H**, the state of the system under study is uniquely defined by the current market state $m \in \mathbf{M}$ and technology $t \in \mathbf{T}$. The immediate decision in period $h \in \mathbf{H}$ is to select a technology $t' \in \mathbf{T}$ for the following period such that expected profits will be maximized over the remaining planning horizon. Optimal expected profits Π_h^* for remaining periods $\{h, h+1, \ldots, H\}$ are written as the recursive relationship

$$\Pi_h^*(m,t) = \max_{t'}\left\{\left(r_{mt} - k_{mt} - c_{tt'}\right) + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^*(m',t')\right\}$$

where $m' \in \mathbf{M}$, $t' \in \mathbf{T}$, and t_0 is the initial state of technology in period $h=0$. The optimal solution to the MAPPS problem is an $M \times T \times H$ decision matrix $\mathbf{D^*}$, where elements $d_{mth}^* \in \mathbf{D^*}$ represent the optimal selection of technology for period $h+1$ when the market prefers scenario *m* and *t* represents the currently installed process technology in period *h*. The solution to a particular instance of a MAPPS problem can be found using standard dynamic programming recursion techniques if the number of possible system states is relatively small, where the definition of "small" is rapidly changing as computational processing speed and availability of fast memory increases. Since the dimensionality of a MAPPS problem grows exponentially with the number of problem inputs, finding optimal solutions may require specialized search reduction techniques for larger problems. Computation times were not a factor for the problems reported in this paper.

Perfect Flexibility and Robust Solutions

Given this formulation model for market preference and technology selection, we define two extreme solutions: perfect flexibility and perfect robustness. These extremes are subsequently shown to provide bounds on the optimal technology selection policy.

Perfect Flexibility

Perfect flexibility is defined as the immediate acquisition and implementation of process technology that maximizes short-term profits π^f when acquisition costs are ignored:

$$\pi^f_{mt} = r_{mt} - k_{mt}$$

Perfect flexibility thus represents the ideal of instantly and costlessly changing process technologies to best match the changing needs of the marketplace. A policy of perfect flexibility is myopic in that it does not consider subsequent periods beyond the current period. When market preferences change, policy of perfect flexibility will immediately adopt the best (highest profit) technology available. Since technology acquisition costs are ignored, the expected profits for a policy of perfect flexibility are calculated as the dynamic programming recursion:

$$\Pi^f_h(m,t) = \max_{t'}\left\{(r_{mt} - k_{mt}) + \sum_{m'} \varphi_{mm'} \Pi^f_{h+1}(m',t')\right\}$$

Because perfect flexibility ignores technology acquisition costs, it is apparent that a perfectly flexible solution will provide higher profits than does an optimal solution that accounts for technological acquisition costs. It can be shown that a policy of perfect flexibility provides an upper bound on profitability (proof in appendix):

> **Theorem 1:** A policy of perfect flexibility provides an upper bound on profitability for the MAPPS problem. That is:
>
> $$\Pi^*_h(m,t) \le \Pi^f_h(m,t)$$
>
> **Corollary 2:** When technology switching costs are free ($c_{tt'}=0$, for all $t,t' \in \mathbf{T}$), then a policy of perfect flexibility is optimal.

From a managerial perspective, perfect flexibility represents the best possible benefit to profit that flexibility can provide. The difference in profit between a perfectly flexible technology and current technology represents the maximum benefit that a more flexible policy can provide. This difference is easily compared against the cost of acquiring a more flexible technology and serves as a screen to determine if the cost of the alternative technology can be justified in improved profits.

Robust Strategies

In contrast to perfect flexibility, a robust strategy is defined as the profit-maximizing selection and acquisition of a single technology that is subsequently retained regardless of changes in market preferences. In determining a robust policy the entire planning horizon must be considered since once a technology is implemented, it cannot be switched regardless of changes in market preferences. Expected profits for a robust policy are found using the dynamic

$$\Pi_1^r(m,t) = \max_t \left\{ \left(r_{mt} - k_{mt} - c_{tt'}\right) + \sum_{m'} \varphi_{mm'} \Pi_2^r(m',t) \right\}$$

programming recursion:

where

$$\Pi_h^r(m,t) = \max_t \left\{ \left(r_{mt} - k_{mt} - c_{tt}\right) + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^r(m',t) \right\}$$

for $h = 2,\ldots,H$ and $\Pi_H^r(m,t) = 0$ for all m, t. Note that in this formulation technology is adopted exactly once, in period 1.

Because a robust policy does not switch technologies regardless of opportunity costs, a robust solution intuitively results in lower profits than does an optimal solution that allows judicious switching. In fact, a policy of perfect flexibility provides a lower bound on optimal profits (proof in appendix):

> **Theorem 3:** A perfectly robust policy provides a lower bound on profitability for the MAPPS problem. That is:
>
> $$\Pi_h^r(m,t) \le \Pi_h^*(m,t)$$
>
> **Corollary 4:** When technology switching costs are sufficiently expensive ($c_{tt'} \to \infty$ for all $t, t' \neq t \in \mathbf{T}$), then a perfectly robust policy is optimal.

The robust policy provides managerial insight into the costs of inflexibility. The difference in expected profits between the current technology and the robust policy represents the opportunity cost of abandoning flexibility. In situations where there exist pressures to reduce flexibility for cost or convenience, this difference provides an estimate of the economic consequences of moving toward inflexibility.

Expected Value of Perfect Flexibility

Given these definitions for robust and perfectly flexible strategies, we can now consider the value of flexibility. We define the *expected value of perfect flexibility V (m,t)* as the difference between the expected profits from perfect flexibility and expected profits from a robust policy when *h=0*:

$$V(m,t) = \Pi_0^f(m,t) - \Pi_0^f(m,t)$$

The expected value of perfect flexibility provides an upper bound on the benefits to profit that flexible technology can possibly provide. In circumstances where *V (m,t)* is a significant percentage of absolute profits, flexibility can provide important benefits to profitability and prudent managers would do well to find ways to improve flexibility. In contrast, when *V (m,t)* is small, flexibility has little potential impact on profitability and will not be of central managerial concern. The expected value of perfect flexibility is a close analog to the expected value of perfect information (EVPI) defined in decision theory (*viz.* Hillier and Lieberman 1995). EVPI measures the expected value of information if uncertain future events could be known with certainty. The expected value of perfect flexibility measures the expected benefit of perfect adaptation to uncertain future events. Better information and improved flexibility can thus be seen as alternate responses to the same general problem of coping with uncertainty.

An Illustrative Example

To illustrate the concepts presented in this paper, we provide the following example adapted from the product-process model of Hayes and Wheelwright (1979a, 1979b). Consider a manufacturer that is planning for the production of an unspecified product line over a planning horizon of 20 quarters (5 years). Discussions with marketing personnel indicate that market demand volume will be steady over the planning horizon, but that one or more of three market preference scenarios may occur:

1. High Mix preference – customers desire a wide variety of product configurations or features
2. Medium Mix preference – customers desire a moderate variety of product configurations or features
3. Low Mix preference – customers do not care about or want a high variety of product configurations

In response to these market preferences, the manufacturer can select between four process technologies:

1. Job Shop technology
    - Capable of high variety
    - High unit production costs
    - Relatively low adoption costs
2. Batch Shop technology
    - Capable of some variety
    - Moderate unit production costs
    - Moderate adoption costs
3. Flow Shop technology
    - Standardized product variety
    - Low unit production costs
    - High adoption costs
4. Flexible Shop technology
    - Low, moderate, or high variety
    - Moderate unit production costs
    - Highest adoption costs

This problem is similar to the product-process model of Hayes and Wheelwright with two exceptions. First, we assume that product demand is constant over time and across market preferences – Hayes and Wheelwright assumed that product preferences correlated with the product life cycle and hence with demand volume. Second, we allow for a flexible technology in the form of a Flexible Shop. The Flexible Shop alternative represents the availability of "mass customization" technologies and processes that can produce a broader range of product configurations at higher production rates than previously possible. Consistent with Hayes and Wheelwright, we assume that production technologies are most effective when paired with matching market preferences:

- Job Shop technology with High Mix market preferences
- Batch Shop technology with Medium Mix market preferences
- Flow Shop technology with Low Mix market preferences
- Flexible Shop technology is less suited for any technology-preference pair above, but is better suited than a mismatch of process technology and market preference (*e.g.*, Job Shop with Low Mix)

These assumptions are illustrated graphically in Figure 1.

Problem Settings

To illustrate the relative performance of optimal, flexible, and robust policies on profitability, we examined three market preference cases:

1. Random Mix market preferences
2. Progression from Low Mix to High Mix market preferences
3. Progression from High Mix to Low Mix market preferences

For each of these cases, only the market transition matrix Φ was varied (Tables 3a – 5a). For the Random Mix case, we assumed no prior knowledge of market preferences so that any one of the three market preference states could be realized in the first period with equal probability. Once a market state was achieved, however, the market was assumed to be "sticky" in that the probability of the market transiting to another state was relatively small in any subsequent period. The High-to-Low Mix progression illustrates the market preference progression of many newly introduced technology products– initial market demand is for high variety, but as the product technology matures and standards are set, demand for variety declines (Hayes and Wheelwright 1979). We assumed that the market initially preferred a High Mix in period 1, but evolved to Medium and Low Mix preferences over time. Finally, the Low-to-High Mix case represents the "product proliferation" phenomena observed with many mature products where the market demands increasing product variety and customization as competition among producers grows (Skinner 1974).

Revenues **R**, production costs **K**, and switching costs **C** were held constant (Table 1) in all experiments to enable easy comparison of results across experiments. Revenues **R** were greatest when production processes and market mix preferences were matched – revenues declined when there is a mismatch (*e.g.*, trying to deliver a high product mix with flow shop technology). Revenues with flexible technology were smaller than when market preferences and production technology are matched, but greater than when there was a mismatch. This reflects the observation that, in practice, flexible production technology is often less productive and more costly to operate than is dedicated technology (Jaikumar 1986). Similarly, production costs **K** were set to be smallest when processes and markets were matched, and largest when most mismatched. The production costs for flexible technology were larger with matched processes and markets, and smaller when mismatched. Finally, technology switching costs **C** increased with the complexity of the technology – job shop technology being the least expensive to acquire and flexible technology the most. Switching costs were assumed to be symmetric since there would be significant abandonment costs when moving from a more expensive to a less costly technology (*e.g.*, from flexible to job shop technology).

Illustrative Results

We obtained the optimal solutions for MAPPS problems using standard backward recursion techniques for dynamic programming (*viz*., Hillier and Lieberman, 1995), as well as values for expected profits. A fragment of the optimal decision matrix **D*** for the Low-to-High Mix case is included in Table 2. For example, if the current market preference is for Medium Mix and the current state of technology is Flow production, then the optimal strategy is to switch to Batch technology in the following period. Expected profits for optimal and robust policies, and for perfect flexibility are tabulated in Tables 3 – 5 and are graphically illustrated in Figures 2 – 4. These figures show the stochastic progression of market preferences and the resulting sequence of technology selection over the planning horizon. In these figures, the vertical bars represent the current state of market preference in each of the 20 periods of the planning horizon, and the three line-graphs represent optimal, robust, and perfectly flexible process selection policies as labeled.

We also undertook simulation studies of the three problem settings described above to better understand and illustrate the stochastic decision processes inherent in our model. One-hundred replications were run for each market mix setting over the twenty periods of the planning horizon – cost, revenue, and profit data was collected for each process selection policy.

Random Mix Case. Results for the Random Mix case are illustrated in Figure 2 and summarized in Table 3. Figure 2a shows a single simulated problem instance and 2b the average of 100 replications. Both illustrate that the optimal technology strategy is to sequentially adopt job shop, batch, flow, and eventually flexible technologies in response to changing market preferences. The economic structure of this case makes it optimal to adopt a sequence of technologies rather than moving directly to flexible technology, but the optimal policy does inevitably move toward flexibility. In contrast, the robust strategy immediately adopts flexible technology despite its higher acquisition costs and potentially higher operating costs – the highly stochastic nature of market preferences requires the most flexible process if only a single technology must be adopted. Finally, a policy of perfect flexibility (labeled "flexible strategy") allows any available technology to be immediately selected to best match the requirements of the marketplace, so that market preference and technology are coincident in Figure 2.

In an uncertain market environment such as the Random Mix setting, the opportunity cost of inflexibility is high. As shown in Table 3b, the expected profit from perfect flexibility is 20,000, expected profits from the robust strategy are 12,000, thus providing an expected value of perfect flexibility of 8,000. Expected profits from the optimal policy are 12,417, so the opportunity cost of inflexibility for the optimal policy is 7,583, or more than 60% of profits. Clearly, increasing flexibility can have a significant impact on profitability in this setting.

High-to-Low Mix Case. Results for the High-to-Low Mix market preferences case are found in Table 4. The transition matrix here indicates that market preferences will move quickly from high to low mix preferences, although the possibility of "backsliding" from low to high exists. Here the optimal policy more closely mirrors a policy of perfect flexibility as illustrated in Figure 3, moving through job shop and batch technologies to flow technology. The expected value of perfect flexibility is again 8,000, and the opportunity cost of inflexibility for the optimal policy is 4,972, or 33% of expected profits. The decreased uncertainty of market preferences means that the optimal strategy is sufficiently flexible to capture more of the expected value of perfect flexibility than in the Random Mix. This reduced uncertainty also changes the robust strategy from one of adopting flexible technology in the Random Mix case to adopting flow technology in the current case. The robust strategy anticipates the inevitable movement of the market to a low mix preference and selects flow technology accordingly.

Low-to-High Mix Case. The Low-to-High mix preference case is a mirror image of the High-to-Low Mix case in that market moves inevitably to a high-mix preference as shown in Figure 4. In this case, however, the optimal policy does not parallel so closely the result for perfect flexibility in that it never adopts flow technology. Instead, the optimal result is to move immediately to batch technology and then eventually to job shop technology when the market migrates to a high mix preference. The expected value of perfect flexibility is again 8,000, and the expected opportunity cost of inflexibility for the optimal solution increases to 6,973, or to 53% of expected profits. The robust policy in this case is to again adopt flexible technology since it provides greater cost reduction opportunities with low and medium mix preferences than does job shop technology.

These examples demonstrate that different market preferences patterns of evolution can result in very different optimal and robust policies, even when revenue and cost structures remain unchanged. While the expected value of perfect information does not vary across the three preference scenarios studied here, the relative value of flexibility compared with optimal policies varies significantly. These results also illustrate the analytical result that perfect flexibility and robust policies form bounds on profitability. These bounds can be managerial useful to indicate the potential benefits of pursuing increased flexibility and the potential costs of reducing flexibility.

Conclusions and Future Research

In this paper we have modeled the evolution of market preferences and the selection of appropriate process technologies. We have defined for the first time the concept of perfect flexibility and related to it, the expected value of perfect flexibility. We also defined a robust policy as one where process selection is invariant over the planning horizon. We have shown that perfect flexibility forms an upper bound for the profitability for MAPPS problems, while a robust policy forms a lower bound.

The concepts introduced in this paper have significant utility for theory and practice. A number of firms and industries are now experiencing a need to reevaluate process flexibility, especially in response to changing business paradigms brought about by the Internet and other communications technologies. While it is becoming easier to capture the dynamic preferences of consumers through use of the Internet and other "digital nervous systems" (Gates 1999), selection of optimal processes and levels of flexibility is conversely becoming more difficult. The abilities to identify optimal process adoption strategies in light of changing marketplace preferences and to model and measure the value of "perfect flexibility" provide effective tools for better process selection and technology adoption planning.

Future extensions of this research include incorporating stochastic technological innovation and stochastic market demand into the model. Ultimately, a model that recognizes all important cost parameters and uncertainties, and allows simultaneous consideration of product variety and process selection, will provide managers with an essential tool for strategic planning.   This paper represents progress in that direction.

References

Balcer, Y. and S.A. Lippman (1984), "Technological Expectations and Adoption of Improved Technology," *Journal of Economic Theory*, 34, 292-318.

Chand, S. and S. Sethi (1982). "Planning Horizon Procedures for Machine Replacement Models with Several Possible Replacement Alternatives," *Naval Research Logistics*, 29, 483-493.

Cox, W. M. and R. Alm (1999), "America's Move to Mass Customization," *Consumers' Research Magazine*, 82, 6, 15-19.

Dertouzos, M., R. Lester, and R. Solow (1990), *Made in America,* Harper Perennial, New York, 232-247.

Fisher, M.L., J.H. Hammond, W.R. Obermeyer, and A. Raman (1994), "Making Supply Meet Demand in an Uncertain World," *Harvard Business Review*, May-June.

Gaimon, C. (1985a), "The Acquisition of Automation Subject to Diminishing Returns," *IIE Transaction*s, 17, 2, 147-155.

Gaimon, C. (1985b), "The Optimal Acquisition of Automation to Enhance the Productivity of Labor," *Management Science*, 31, 1175-1190.

Gaimon, C. (1994), "Uncertainty and the Acquisition of Capacity: A Competitive Analysis," Computers & Operations Research, 21, 10, 1073-1085.

Gates, B. and C. Hemmingway (1999), *Business @ the Speed of Thought; Using a Digital Nervous System*, Warner Books, New York.

Hayes, R., and S. Wheelwright (1979a), "Link Manufacturing Process and Product Life Cycles," *Harvard Business Review,* January-February.

Hayes, R., and S. Wheelwright (1979b), "The Dynamics of Process-Product Life Cycles," *Harvard Business Review*, March-April.

Hesler, M. (1999), "Bridge the Gap Between Online and Off-Line Customer Profiling and Personalization," *Target Marketing*, 22, 11, 57.

Hillier, F., and G. Lieberman (1995), "Markov Decision Processes," Chapter 19, *Introduction to Operations Research*, sixth edition, McGraw Hill, New York.

Li, S. and D. Tirupati (1997), "Impact of Product Mix Flexibility and Allocation Policies on Technology," *Computers and Operations Research*, 24, 611-626.

Manne, A. S. (1961), "Capacity Expansion and Probabilistic Growth," *Econometrica*, 19, 632-649.

Monahan, G., and T. Smunt (1989), "Optimal Acquisition of Automated Flexible Manufacturing processes," *Operations Research* 37(2), Mar-Apr, 288-300.

Newell, A., and H. Simon (1972), *Human Problem Solving*, Prentice Hall, Englewood Cliffs, NJ.

Pierskalla, W. and J. Voelker (1976), “A Survey of Maintenance Models: Control and Surveillance of Deteriorating Systems,” *Naval Research Logistics Quarterly*, 23, 353-388.

Rajagopalan, S. and A.C. Soteriou (1994), “Capacity Acquisition and Disposal with Discrete Facility Sizes,” *Management Science*, 40, 903-917.

Rajagopalan, S., M. Singh, and T. Morton (1998), “Capacity Expansion and Replacement in Growing Markets With Uncertain Technological Breakthroughs,” *Management Science* 44(1), January, 12-30.

Rajagopalan, S. (1999), “Adoption Timing of New Equipment with Another Innovation Anticipated,” *IEEE Transactions on Engineering Management*, 46, 14-25.

Skinner, C.W. (1974), “The Focused Factory,” *Harvard Business Review*, May-June.

Sweat, J. (1999), “GM Races to Keep Up with Buyers,” *Informationweek*, 754, 368.

Proof of Theorems

Proof of Theorem 1

Proof. Note that $r_{mt} - k_{mt} - c_{tt'} \leq r_{mt} - k_{mt} - c_{tt}$ for t' . Therefore, $r_{mt} - k_{mt} - \min_{t'} c_{tt'} \leq r_{mt} - k_{mt} - c_{tt}$, which can be written as

$$\max_{t'}\{r_{mt} - k_{mt} - c_{tt'}\} \leq r_{mt} - k_{mt} - c_{tt}$$

Since $\Pi_H^*(m,t) = \max_{t'}\{ r_{mt} - k_{mt} - c_{tt'}\}$ and $\Pi_H^f(m,t) = r_{mt} - k_{mt} - c_{tt}$, the result is true for $h=H$. Assume the result is true for $h+1$. Then

$$\begin{aligned}
\Pi_h^*(m,t) &= \max_{t'}\left\{r_{mt} - k_{mt} - c_{tt'} + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^*(m',t')\right\} \\
&\leq \max_{t'}\left\{r_{mt} - k_{mt} + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^*(m',t')\right\} \\
&\leq \max_{t'}\left\{r_{mt} - k_{mt} + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^f(m',t')\right\} \\
&= \Pi_h^f(m,t)
\end{aligned}$$

The first inequality follows from the fact that $c_{tt'} \geq 0$ for all t'. The second inequality follows from the induction hypothesis. □

Proof of Theorem 2

Proof. Since $\Pi_H^r(m,t) = \max_{t'} r_{mt} - k_{mt} - c_{tt} = \Pi_H^*(m,t) = r_{mt} - k_{mt}$ for all m, t, the result is true for $h=H$. Assume the result is true for $h+1$. Then

$$\begin{aligned}
\Pi_h^r(m,t) &= \max_{t'}\left\{r_{mt} - k_{mt} - c_{tt} + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^r(m',t')\right\} \\
&\leq \max_{t'}\left\{r_{mt} - k_{mt} - c_{tt'} + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^r(m',t')\right\} \\
&\leq \max_{t'}\left\{r_{mt} - k_{mt} - c_{tt'} + \sum_{m'} \varphi_{mm'} \Pi_{h+1}^*(m',t')\right\} \\
&= \Pi_h^*(m,t)
\end{aligned}$$

□

TABLES

Table 1

Revenue and Cost Matrices

Market \ Technology	Job Shop	Batch Shop	Flow Shop	Flex Shop
Start				
High Mix	1,500	1,250	1,000	1,400
Med Mix	1,250	1,500	1,250	1,400
Low Mix	1,000	1,250	1,500	1,400

1a. Revenue Matrix, **R**

Market \ Technology	Job Shop	Batch Shop	Flow Shop	Flex Shop
High Mix	500	750	1,000	600
Med Mix	750	500	750	600
Low Mix	1,000	750	500	600

1b. Production Cost Matrix, **K**

Technology	Job Shop	Batch Shop	Flow Shop	Flex Shop
None	1,000	2,000	3,000	4,000
Job Shop	0	1,000	2,000	3,000
Batch Shop	1,000	0	1,000	2,000
Flow Shop	2,000	1,000	0	1,000
Flex Shop	3,000	2,000	1,000	0

1c. Technology Adoption Cost Matrix, **C**

Table 2

Fragment of Optimal Decision Matrix **D***

Market Preference	**Current Technology**	**Switch to Technology Period 10**	**Period 11**	**Period 12**
Low Mix	Job Shop	Job Shop	Job Shop	Job Shop
Low Mix	Batch	Batch	Batch	Batch
Low Mix	Flow	Batch	Batch	Batch
Low Mix	Flexible	Flexible	Flexible	Flexible
Med Mix	Job Shop	Batch	Batch	Batch
Med Mix	Batch	Batch	Batch	Batch
Med Mix	Flow	Batch	Batch	Batch
Med Mix	Flexible	Flexible	Flexible	Flexible
High Mix	Job Shop	Flow	Flow	Flow
High Mix	Batch	Batch	Batch	Batch
High Mix	Flow	Flow	Flow	Flow
High Mix	Flexible	Flexible	Flexible	Flexible

Low-to-High Mix Market Preference Case

Table 3

Random Market Mix Preference Case

Preference	High Mix	Med Mix	Low Mix
Start	0.33	0.33	0.33
High Mix	0.80	0.10	0.10
Med Mix	0.10	0.80	0.10
Low Mix	0.10	0.10	0.80

3a. Market Preference Transition Matrix, $\boldsymbol{\Phi}$

Expected Profits	Robust Policy	Optimal Policy	Perfect Flexibility
Total Expected Profit	12,000	12,417	20,000
Opportunity Cost of Inflexibility	8,000	7,583	Na
Expected Value of Perfect Flexibility	na	na	8,000

3b. Expected Profits

Simulated Costs and Profit	Robust Policy	Optimal Policy	Perfect Flexibility
Revenues	28,000	28,450	30,000
Operating Costs	12,000	11,500	10,000
Switching Costs	4,000	4,000	0
Profit	12,000	12,900	20,000
Opportunity Cost of Inflexibility	8,000	7,100	Na
Value of Perfect Flexibility	na	na	8,000

3c. Simulated Costs and Profits (single trial)

Table 4

High Mix to Low Mix Market Preference Case

Preference	High Mix	Med Mix	Low Mix
Start	1.00	0.00	0.00
High Mix	0.80	0.15	0.05
Med Mix	0.05	0.80	0.15
Low Mix	0.00	0.05	0.95

4a. Market Preference Transition Matrix, Φ

Expected Profits	Robust Policy	Optimal Policy	Perfect Flexibility
Total Expected Profit	12,000	15,028	20,000
Opportunity Cost of Inflexibility	8,000	4,972	Na
Expected Value of Perfect Flexibility	na	na	8,000

4b. Expected Profits

Simulated Costs and Profit	Robust Policy	Optimal Policy	Perfect Flexibility
Revenues	26,000	28,850	30,000
Operating Costs	14,000	11,250	10,000
Switching Costs	3,000	3,000	0
Profit	9,000	14,600	20,000
Opportunity Cost of Inflexibility	11,000	5,400	Na
Value of Perfect Flexibility	na	na	11,000

4c. Simulated Costs and Profits (single trial)

Table 5

Low Mix to High Mix Market Preference Case

Preference	High Mix	Med Mix	Low Mix
Start	0.00	0.00	1.00
High Mix	0.95	0.05	0.00
Med Mix	0.15	0.80	0.05
Low Mix	0.05	0.10	0.80

5a. Market Preference Transition Matrix, Φ

Expected Profits	Robust Policy	Optimal Policy	Perfect Flexibility
Total Expected Profit	12,000	13,027	20,000
Opportunity Cost of Inflexibility	8,000	6,973	Na
Expected Value of Perfect Flexibility	na	na	8,000

5b. Expected Profits

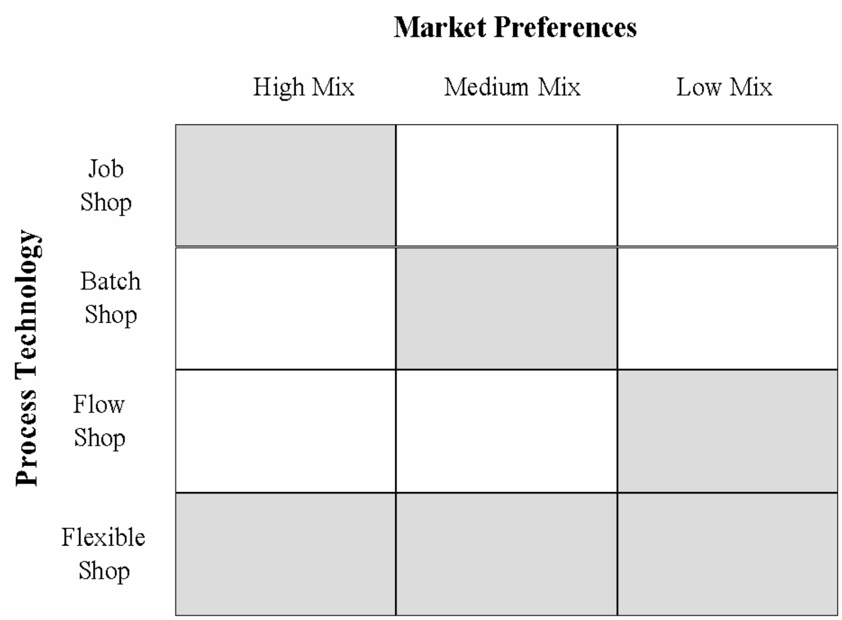
Simulated Costs and Profit	Robust Policy	Optimal Policy	Perfect Flexibility
Revenues	28,000	28,050	30,000
Operating Costs	12,000	12,000	10,000
Switching Costs	4,000	3,000	0
Profit	12,000	13,050	20,000
Opportunity Cost of Inflexibility	8,000	6,950	Na
Value of Perfect Flexibility	na	na	8,000

5c. Simulated Costs and Profits (single trial)

FIGURES

Figure 1

Structure of Market Preferences and Process Technologies



Shaded blocks represent preferred pairings of market preference and process technology.

Figure 2

Random Mix Market Preference Case

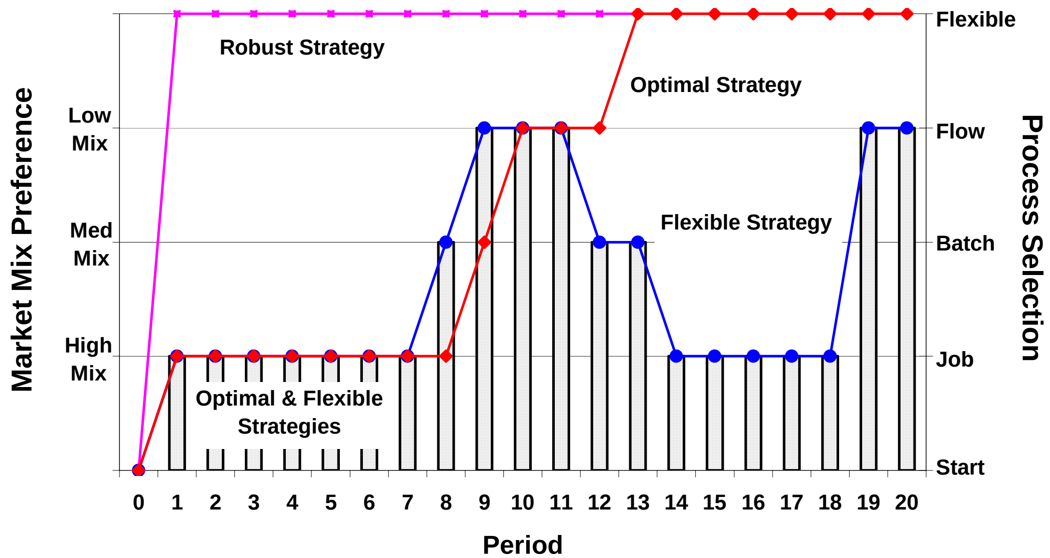


Figure 2a – Example of a Single Trial

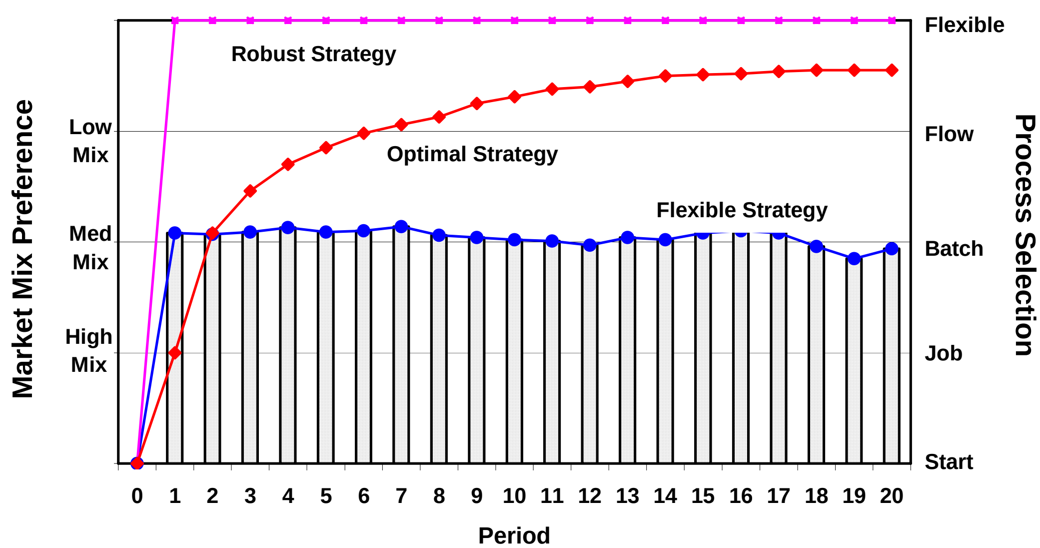


Figure 2b – Average of 100 Trials

Figure 3

High-to-Low Mix Market Preference Case

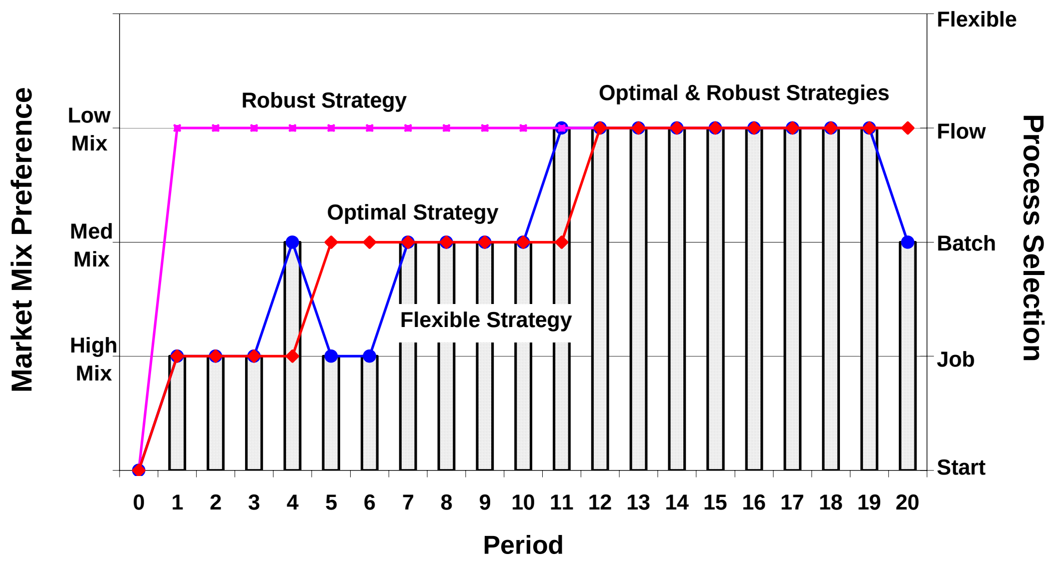


Figure 3a – Example of a Single Trial

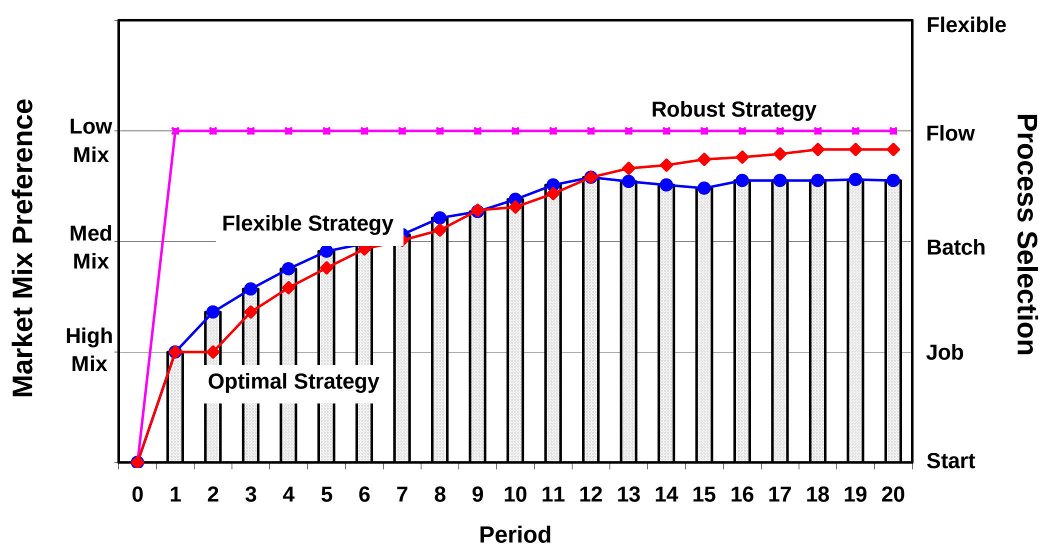


Figure 3b – Average of 100 Trials

Figure 4

Low-to-High Mix Market Preference Case

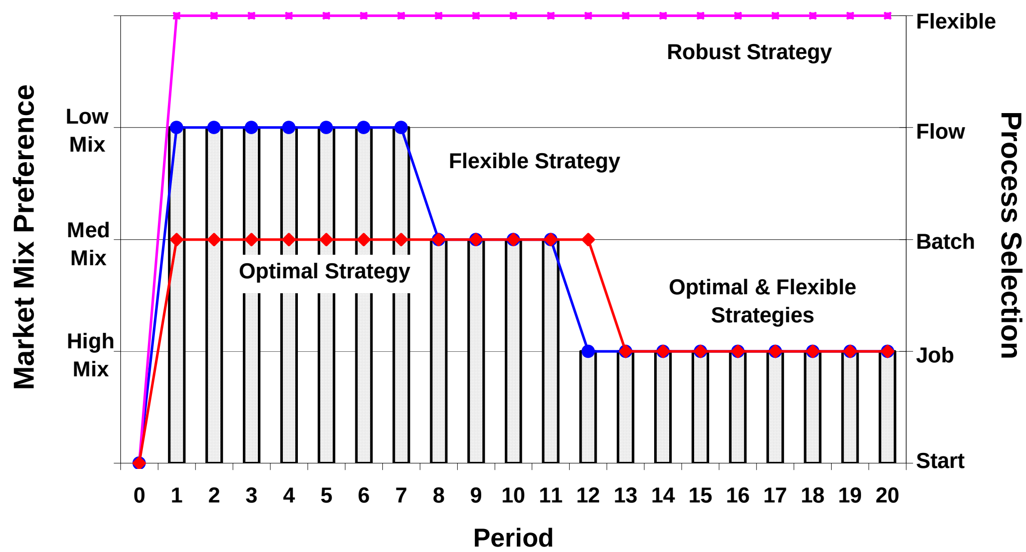


Figure 4a – Example of a Single Trial

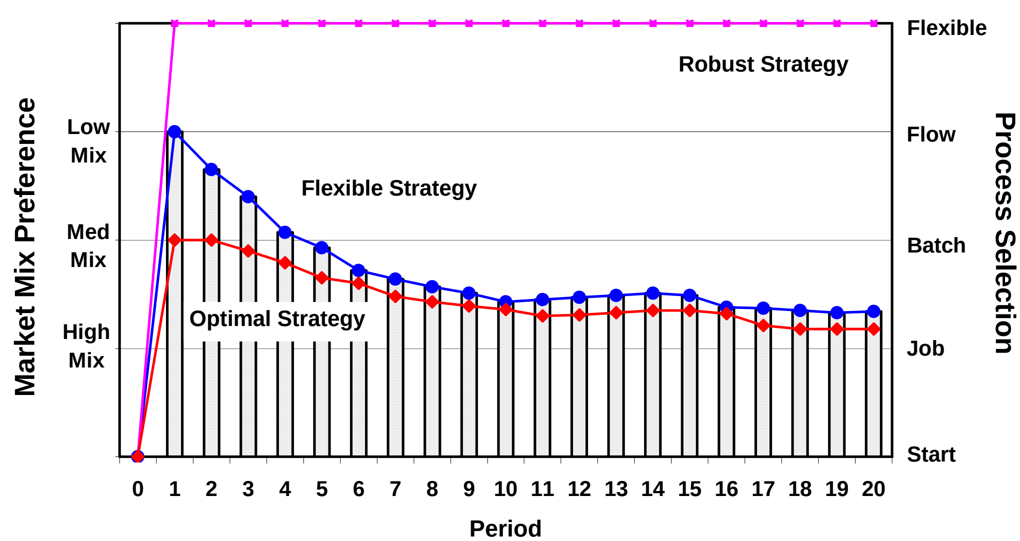


Figure 4b – Average of 100 Trials