REAL OPTION MODELS FOR MANAGING MANUFACTURING SYSTEM CHANGES IN THE NEW ECONOMY

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ABSTRACT

The manufacturing environment is becoming increasingly dynamic with upsurges in electronic-commerce, supply chain management, forecasting, and procurement and resource planning. It also includes trends toward more process data acquisition and analysis, shorter production runs, and more stringent quality requirements. These drivers lead to an opportunity for companies to collect and use information to identify changes that will affect their manufacturing systems. In conjunction with an industry partner who produces home fashion products, we developed a case-study that highlights four major manufacturing transitions: new product introduction; moving a product from research and development (R&D) to commercialization; new plant location; and starting or restarting production of existing products. These types of changes cross many levels of the operation - including the product level, plant level, and organizational level - and typically present significant operational challenges. We use this case-study to motivate the theoretical and applied research needed to support a real option framework for system changes in manufacturing. The key elements of our framework are to quantify manufacturing changes, develop a real option model for these activities, value the options to identify the best scenarios, and integrate these elements so that we can monitor and manage the overall process. The advantage of this approach is that it allows us to directly incorporate a market driven perspective, tying the manufacturing operations with the organizational economic goals.

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INTRODUCTION

The rise of e-commerce has introduced a new dynamic of competing on "Internet-time." We are beginning to see the advancement of new business models based on e-commerce including "judo strategy," "e-business," and "business-to-business (B2B)" (e.g., see Yoffie and Cusamano (1999) and Leebaert (1998)). E-commerce presents opportunities to develop and deliver new products and services to customers and opportunities to establish direct links to customers and suppliers to make transactions. E-commerce will change *everything* about how a corporation operates: "[It] will change the relationship between consumers and producers in ways more profound than you can yet imagine" (Hamel and Sampler (1998)). In many aspects, it is also propelling new models in supply chain management, forecasting, and marketing, purchasing, and resource planning.

In conjunction with these dynamics, the manufacturing systems themselves will also have to change. We have already seen evidence of trends toward more process data acquisition and analysis, shorter production runs, and more stringent quality requirements. In this paper, we often use the word *transition* because it connotes change as a *process*. In order to better manage this process, we first recognize that more decision-making and operational action at different points in time are required during transitions than in steady-state periods. We also need to better understand the value of flexibility. While these ideas are conceptually comfortable, the modeling and application of these ideas are somewhat subtle.

To begin the journey, consider FIGURE 1. It illustrates the operational level - which includes product design, scheduling, production, and process control - of manufacturing systems. Typically, we expect these functions to come together to make a product and, hopefully, profit for the organization. In conjunction with an industry partner who produces home fashion products, we developed a case study that highlights four major manufacturing transitions: new product introduction; moving a product from research and development (R&D) to commercialization; new plant location; and starting or restarting production of existing products.

As our technology has advanced and the manufacturing environment has become more dynamic, systems have become more complex and the consequences of transitions have become more difficult to analyze. Pressures frequently come from outside of manufacturing to make system changes – this is indicated in FIGURE 1 by the e-commerce circle. (E-commerce is not the only pressure, of course, but we use it to represent the many other dynamics connected with it as mentioned above.) The issue is that the changes are often made without the benefit of much information about the factors that influence the manufacturing operational levels or what they cost. Furthermore, it is not well understood what the true cost or benefit may be of delaying a transition or changing the decisions made within one. In short, economic aspects of changing the manufacturing system in a dynamic environment need more robust consideration.

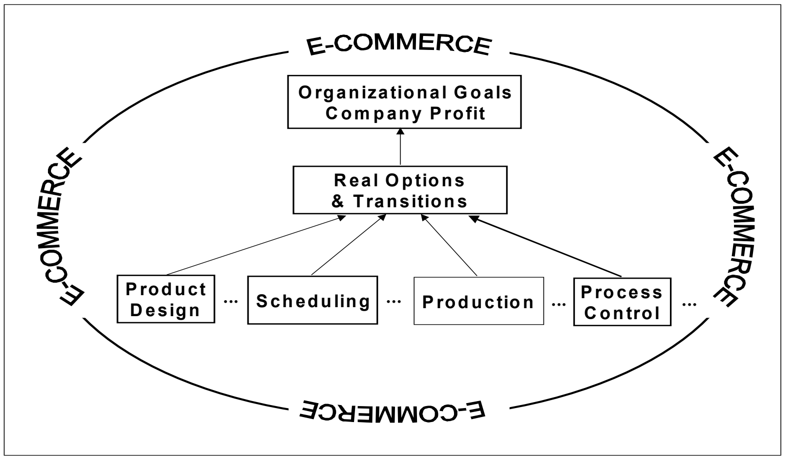

Figure 1: Relationship among manufacturing transitions, e-commerce, and operational level.

The purpose of our paper is to present a framework for manufacturing system changes that will improve operational decision-making. Within this framework, we present the dynamics of the change as *real options.* The financial definition of an option is a right to buy or sell a specific asset by paying a prespecifed price on or before a specific maturity date. When the underlying asset is a non-financial one, the contract is referred to as a "real option". In a nutshell, options theory says that when the future is highly uncertain, it pays to have a broad range of options open. At a fundamental level an option is the right to take some action in the future. If the option can be exercised before maturity, it is called an *American* option; if only at maturity, it is called a *European* option. There are also more complex forms such as Bermudan options, compound options, Asian options, barrier options, lookback options and a host of others (e.g., see Luenberger (1998), (Trigeorgis (1996) or Ross (1999)). Luehrman (1998a) gives an introduction to calculating option values using a generic capital budgeting project and Luehrman (1998b) follows up with a discussion of real options from a strategic standpoint.

We will discuss the theoretical and applied research needed to support a real option framework for system changes in manufacturing. In order to use real options to capture these changes, there are three primary research questions that must be undertaken:

How do we identify and model manufacturing system flexibility in ways that work for financial valuation?

How do we bring the discipline of the financial markets to internal valuation and decision-making?

How do we evaluate the solution methods available for calculating option values and select the best solution method for a given specific transition problem?

These questions drive our framework to identify the capacity for critical, more complete information through e-commerce and the impact it will have on manufacturing systems, establish the mathematical representation of manufacturing system changes using real options models, quantify manufacturing activities and model transitions, and value the options to identify the best scenarios. These research issues and our approach will be illustrated using a case study of a major home fashions manufacturer.

This area of research is still in the process of development. Even so , in this paper we can already show that the benefits of using an options approach will increase the understanding of the impact of extending or collapsing the time it takes to implement changes. In addition, it provides a method of effective economic analysis of manufacturing operational aspects that have previously been done only through guesswork. We also discuss how the research elements may be integrated so that the overall process can be monitored and managed. The advantage of this approach is that it allows us to directly incorporate a market driven perspective, tying the manufacturing operations with the organizational economic goals. We hope that this framework will also serve as a motivator for others to conduct future research in this area.

This paper is organized as follows: First, we present the case study that involves making changes in the manufacturing system that may be motivated by e-commerce and other outside forces. Then, we give an overview of the approaches in decision analysis and the motivation for selecting the real options approach for this problem. Next, the main issues for research development are discussed with several examples that tie to the industry case study. Finally, we provide our concluding thoughts on the potential impact of future research and avenues for transferring the research to practice.

COMMON SYSTEM CHANGES IN MANUFACTURING OPERATIONS

In order to illustrate the transitions and the economic considerations that face manufacturers in this economy, we will use the case of HomeWindow Fashions.[1] HomeWindows manufactures several types of window blinds including horizontal and vertical blinds, and wood and fabric blinds. They are a very vertically integrated company that also produces many of the components such as the metal railing and plastic levers needed for assembly. FIGURE 2 presents the basic story of the case in four steps that illustrate how the manufacturer is affected by e-commerce, responds to changes in business conditions, and plans manufacturing operations accordingly.

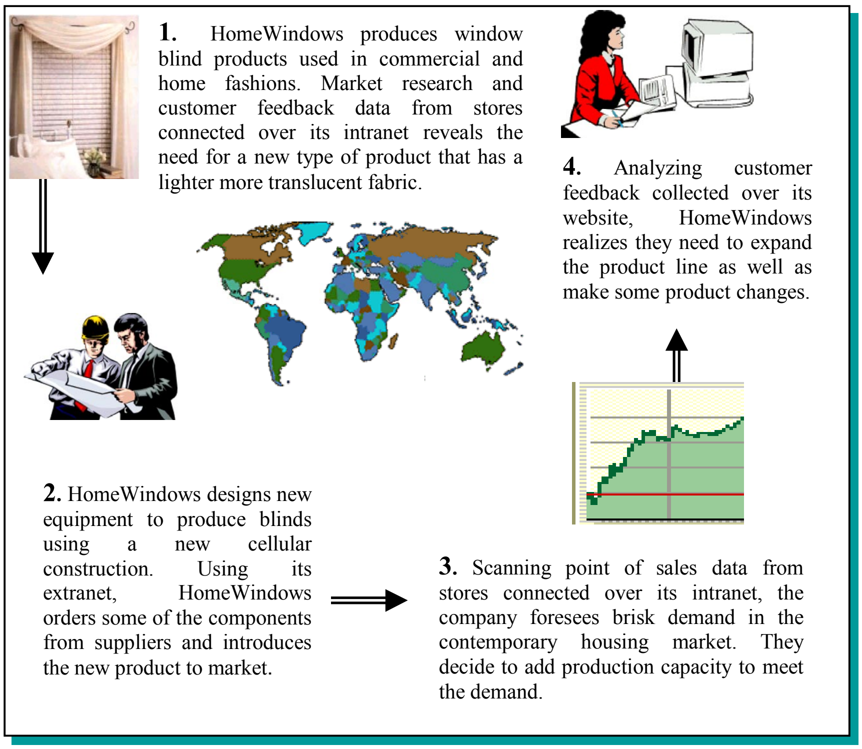

FIGURE 2. Doing business in the Internet age: The case of a consumer products manufacturer.

Step 1: New Product Introduction. The company gets feedback from customers about its current products, and can introduce new products using the customer feedback information. They analyze customer feedback data along with current sales data from stores connected over its intranet, and consider introducing a new product based on the customer feedback. The intranet helps the manufacturer to respond to the customer needs faster and with better products. Often new products are offered in response to customer requests or feedback about what they did or did not like about a company's current product. To meet these needs, of course, product design is an elemental function.

Step 2: R&D to Commercialization. The company needs to do some additional R&D on how to include features their customers desire and develop a new production plan. If customers disliked the product or want an entirely new product, the issue may become one of initiating a new R&D effort. Another major consideration in this step is understanding the timing of marketing the product and integrating that perspective with the manufacturing operation plans. Historically R&D was a realm where the engineers and technicians could dream in isolation and without many pragmatic pressures. This situation has changed. In the present environment, the R&D, product development, manufacturing, and sales/marketing functions must be intertwined because to do otherwise wastes valuable resources and exposes the enterprise to risk of obsolescence (Herath and Park (1999)).

Step 3: New Plant Location. The manufacturer foresees brisk demand in their new product. If they need to add a new production capacity, what transition do they have to go through to meet the additional demand? Is a new production facility required? If they foresee a great deal of fluctuation in demand, they need to make a decision on adding production capacity now or wait until they are more convinced about the demand. Opening up a new manufacturing plant is, of course, a significant business investment. There are also transitions associated with new plant locations for existing enterprises that might be decided upon to support subassembly, to meet additional product demand, or to centralize operations.

Step 4: Re/start of Production. The manufacturer receives customer satisfaction and suggestion data from the intranet, and uses this data to extend and improve the existing product line. With an extended product line and only one processing line, if the customer order is for products that are not currently in production, the cost of starting a new product should be addressed in the pricing. An analogy for the transition period that occurs during a production start or restart is a car that has to "warm-up" for some amount of time before it can perform at its best level. Of course, the operator can drive the car as soon as it is started, but it may take some time to get the best acceleration performance.

Similarly, in most industry settings, after the system is started, reasonable parts may be produced from the line, but closer inspection may reveal that they do not meet specifications.

These four steps outline a very smooth path of introducing a new product in response to a demand that was recognized via e-commerce. However, one particular product that started along this path in January 1999 met with several problems that resulted in a large dollar loss for the company by years' end. The core problem was that management did not know the true manufacturing costs associated with the transitions that were required in production. We return to this case study for six examples that are throughout this paper. These examples illustrate that since change is often noninstantaneous, the decisions that are associated with the change must be viewed in a context that will span time, reflect the actual manufacturing activity, and recognize the value of flexibility

AN OVERVIEW OF ALTERNATIVE DECISION METHODOLOGIES

In evaluating uncertain future financial outcomes due to manufacturing transitions, there are three competing methodologies: (1) decision analysis, (2) capital asset pricing, and (3) real option valuation. In principle, implementation of these methods can be accomplished with the same analytical techniques. However, since the underlying or natural assumptions as well as the values and probabilities used in each type of analysis differ, the results may differ among the techniques. Of course, the practical value of using any type of analysis hinges on how the analysis is performed (Teisberg (1995)).

Decision analysis: Decision analysis is a straightforward way to lay out future decisions and sources of uncertainty (usually in a tree format). Decision analysis is not designed to focus on the market value of a project or strategy. It is designed to calculate the value of a project or decision to an individual decision maker, taking into account the information at his or her disposal, his or her subjective assessments of future uncertainty, and reflecting his or her utility function. The risk attitude of the particular decision maker is thus quantified through his or her subjective utility function. Under the decision theory, we select the investment alternative providing the highest expected utility based on certain axioms of consistent, rational behavior (von Neumann and Morgenstern (1947)).

Capital Asset Pricing: This approach adopts the perspective of the investors in the market. The impact of an investment decision is not measured in terms of its subjective worth to the decision maker, but rather in terms of its value to the market or its contribution to investor wealth. What matters is the risk attitude of the market which is typically captured by adding a "market risk premium" to the risk-free interest rate when calculating the risk-adjusted rate used to discount the expected future cash flows. The risk premium reflects the market's attitude toward the risk inherent in those cash flows and must equal the extra return expected in the market by similar investments of comparable risk (Kasanen and Trigeorgis (1995)).

Real options analysis: A real option framework of decision-making is based on the opportunity to make a decision after we see how events unfold. With the real option approach, we model the cash flows from the completed project to estimate the value of the underlying asset, and then use that estimated asset value as an input to the option valuation. Real option pricing can be seen as a special (risk-neutral) version of decision analysis that recognizes market opportunities to trade and borrow. It is the version of decision analysis that has adopted the market perspective, allowing determination of expected values using risk-neutral probabilities and discounting at a risk-free rate (Black and Scholes (1973) and Amram and Kulatilaka (1999)).

As can be seen above, the major difference among these approaches is the perspective used to determine value, which may then lead to differences in accounting for risk. Certainly, there is no dominant choice among these methods for all cases. Under certain conditions, decision analysis plus some other treatments (such as risk-adjusted probabilities) may yield results that are consistent with the option approach (Smith and Nau (1995)). However, both decision analysis and capital asset pricing analysis are based on fixed investment scenarios, such that there is no clear way to reconcile, aggregate, or choose between scenarios. Furthermore, many of the changes taking place in manufacturing operations are most likely market driven.

An important motivator for this work is that strategic investment decisions often require an allocation of resources that is irreversible (or costly to reverse), and therefore, flexibility to change the course, pace or use of the project in the future may be valuable to the firm if the future unfolds in an unexpected way. This makes the options approach the most natural choice for modeling manufacturing system changes in a dynamic environment.

RESEARCH ISSUES FOR A REAL OPTIONS FRAMEWORK FOR MANUFACTURING SYSTEMS

In this section, we will expand on the research needed for modeling manufacturing system as real options. Figure 3 shows the framework of the connections involved in the research area. We assume that the e-commerce environment will be a fact of doing business in the new economy. Thus, in a broad sense, e-commerce is viewed as an input that will affect manufacturing operations.

Information on system changes will come from this environment that includes the supply chain, forecasting, and marketing and purchasing. Even though the primary focus of this paper is not on information technology or new data mining techniques, an understanding of the data generating process (as discussed in Gebase (1994) and Weiss and Indurkhya (1997), for example) will be useful to screen or structure data that may be needed for the real options model development. For example, many companies will soon be able to watch and learn as customers pick through features and specifications for their products. They will also able to set up marketing surveys where buyers can reveal information pertinent to suppliers. As companies like General Motors and Lands' End realize, these data may be more valuable than any marketing data ever collected (Port (1999)). To fully recognize this value, there must be a clear plan about the manufacturing response.

These factors will have a direct impact on manufacturing at all levels of the operation including design, scheduling, production, and quality engineering. Our goal is to quantify manufacturing changes, develop a real option model for these activities, value the options to identify the best scenarios, and integrate these decision elements so that we can improve decision making for the overall manufacturing operation. In the following subsections, we discuss the specific elements needed to define this research direction.

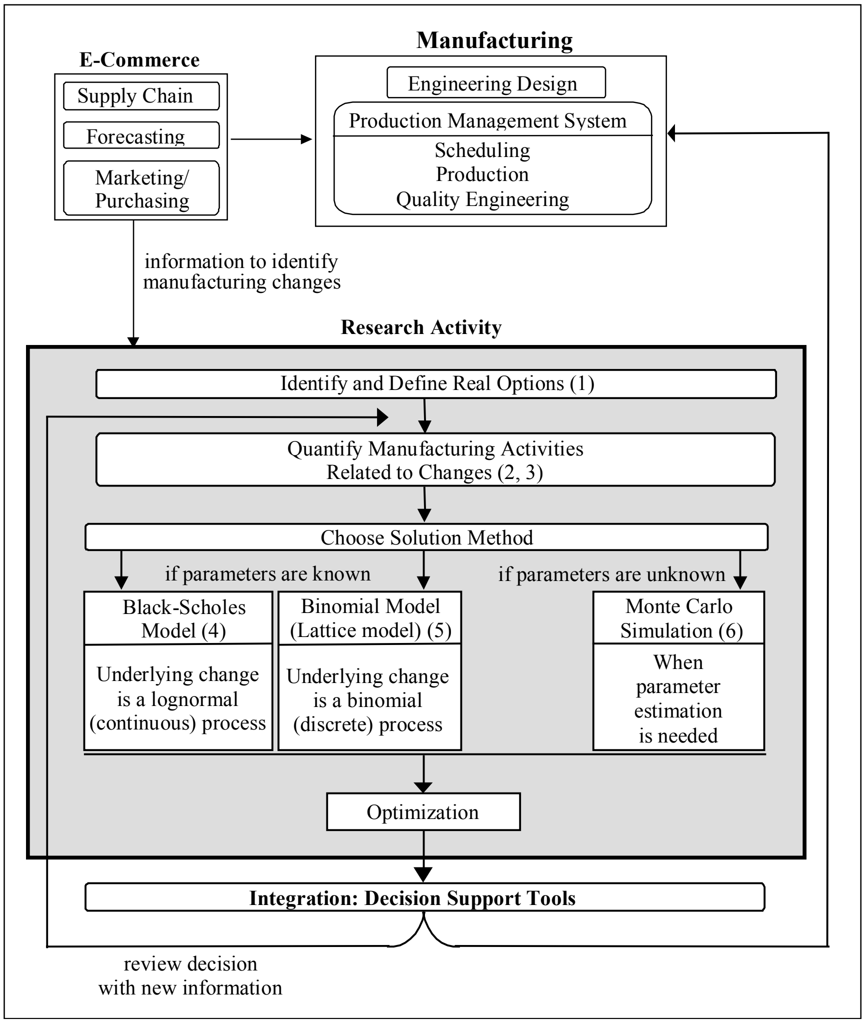

FIGURE 3. Framework of research activity and relationship to e-commerce and manufacturing. (The numbers in parenthesis refer to the examples given in the following sections.)

DEVELOPING REAL OPTION MODELS FOR MANUFACTURING SYSTEM CHANGE

The first issue is to develop a prototype real-option model for manufacturing system change. The general idea is to connect manufacturing changes with the real option variables. As a starting point for illustrating how to relate manufacturing transitions to the option model, we will consider how a European call option model can be related to a change to increase production. There are six variables for the valuation of the European call option. These variables are linked to the production transition as shown in TABLE 1.

TABLE 1. Relating a manufacturing change to a European call option.

Production Change	European Call Option	Variable
Value of the production run's underlying cash flows	Stock price	S_t
Expenditure required to make the production run	Exercise price	X
Length of time decision to make the production run can be deferred	Time to expiration	T
Time value of money	Risk-free rate of return	r_f
Mean and variance of transition characterizations	Mean and variance of returns on stock	μ, σ^2

Given that the production project will result in a finished product, we can interpret the value as the option's *stock price at time t* (S_t). A source of value depletion is the discounted present value of material costs in products that do not meet specifications. The required labor and materials, for example, are expenditures that are similar to the *exercise price (or strike price)* (X). The length of time for which the decision to make the change can be deferred can be defined such that the production is completed by the due date or promised date and is analogous to the *time to expiration* (T). The time value of money represents the *risk-free rate of return* (r_f). The mean and variance of transition characterizations is similar to *mean and variance of returns on stock* (μ, σ^2). This is a source of volatility and uncertainty in that if we put off the decision to start the production, the process may be characterized by a different transition. Under the European call option, the net present value (NPV) of the option on its expiration is given by (Fu and Hu (1995))

$$J_T = \max(S_T(\mu, \sigma^2) - X, 0)e^{-r_f T} \quad . \tag{1}$$

This equation says that the value of the option will be the greater of the difference between the stock price and exercise price multiplied by an adjustment term that takes into account the time value of money. We note that other more complex options may be more suitable for some transitions and should be explored.

Example 1: HomeWindows' point of sales data suggested to managers that the facility's capacity may need to be increased (see FIGURE 2). The current capacity is fixed at C. An increase in capacity would allow two new products, Product A and Product B, to be introduced. In the real options literature, the price P is assumed to be a function of the aggregate demand, *D,* for a product that follows a given distribution and is a function of time, *t.* Now S_t is simply a function of demand, capacity, and variance. With this model, it is possible to determine the NPV for the option of changing capacity at a certain time. If the option value is very small or zero, it indicates that the manufacturing transition should take place in the near future or immediately.

QUANTIFYING MANUFACTURING ACTIVITIES

The second issue is to define the detailed cash flow components that will be used to calculate the NPV of an option (S_t in Equation (1)). With the estimated cash flow series, we will be able to compare alternatives for product types, plant locations, etc. By comparing the alternatives, options can be evaluated, so that decisions can be made for those options. As the first step of constructing the cash flow series, we need a cost model for manufacturing activities during the transient period to improve the prediction of the short-term and long-term effects of production delay due to the transition period. This type of model would also help identify ways to *influence* the underlying variables that determine option value. In all of the options models, we need to investigate ways to determine the value of the parameters that relate to the transition. (We consistently use the viewpoint of the cost model but this can be translated to a profit model when that viewpoint is more helpful.)

Several economic evaluation models for advanced manufacturing systems have been developed in an effort to quantify manufacturing activities in dollar terms (e.g., see (Park (1987), Son and Park (1987), Park and Son (1988), Park and Kim (1995), and Kim and Park (1997)). If we use the activity-based-costing (ABC) as the underlying cost classification, we may group the elements of product cost in three areas:

Costs as Needed: The costs elements are consumed as needed. Direct material and labor are the two major elements in this category.

Activity Costs: Activity costs are those that are directly caused by performing activities on product. In this category, we have eight activity costs:

(1) processing, (2) tooling, (3) quality control, (4) setup, (5) material handling, (6) inventory handling, (7) purchasing order, and (8) software-related activity.

Non-Activity Costs: There are several non-activity costs (or opportunity costs) that are not directly caused by performing activities on products: (1) waiting time cost, (2) inventory holding cost, (3) idle time cost, and (4) unused activity cost.

These cost elements will be a key to developing the option models. It will also be important to build upon the work of American options and cost estimating using forecasting to improve the accuracy of the cost elements. Some of the necessary groundwork has been laid by Kumar (1999), Hazelrigg (1977), Hazelrigg and Hubband (1985), and Hazelrigg (1992)).

Example 2: In the HomeWindows process, there are a number of variables that influence the cost estimates that also generate new options. In case of a new product introduction, some of the variables to be used in the cost model are 'future demand for that product', 'price of the product in the competitive market', and 'setup costs for the new product'. The information needed to build models based on these variables can be obtained from historical databases or mining strategies associated with e-commerce.

QUANTIFYING CHANGE DURATION

The third issue is to develop models of change duration. The length of the transition period (T in the options model (Equation (1)), is another important parameter that needs to be determined. Transition dynamics are usually characterized by high-levels of nonlinearity, disturbance, uncertainty, and interaction among variables. Such transitions may involve a shift in the level of many factors (e.g., market share, production capacity, or even input and output materials). If the production capacity must be changed to meet an increased demand, the transition then would be from one capacity level to another. In all but the simplest systems, such a level shift will not occur instantaneously because of underlying dynamic behavior in the system. One way to model this type of level shift is to use a step input for the change, which is given by:

$$U_t = \begin{cases} 0 & \text{if t < c;} \\ \text{M otherwise,} \end{cases} \tag{2}$$

where c is the time at which the step change of magnitude M occurs. The dynamic behavior could then be represented as a first-order Laplace transfer function (in the s domain) given by

$$G(s) = \frac{K}{\tau s + 1} \tag{3}$$

where K is the steady-state process gain and τ is the process time constant. The step input change U_t to a first-order process $G(s)$ appears as an exponential rise to a new level. This type of model has its foundation in process dynamics theory which has been widely used to represent systems that change over time (see, e.g., Box et al. (1974), Box et al. (1994), Ogunnaike and Ray (1994), and (Seborg et al. (1989)).

Of course, in reality, the dynamic behavior of the transition process would be confounded by noise variation and uncertainty. We can characterize the noise by an autoregressive integrated moving average (ARIMA) model given by

$$\Phi_p(B)\nabla^d y_t = \Theta_q(B)u_t \tag{4}$$

where Φ_p is the autoregressive operator, Θ_q is the moving average operator, B is the backward shift operator defined by $B^m z_k = z_{k-m}$, and ∇ is the difference operator defined by $\nabla = 1 - B$ (Box et al. (1994)).

By combining Equations (3) and (4), we can develop a model of a noisy dynamic system to characterize manufacturing processes during transitions (Nembhard (1998), Nembhard and Mastrangelo (1998), and Nembhard and Park (1999)).

It is necessary to explore variations of this model that may better represent particular types of changes in manufacturing systems. A key point is that the model will help us determine what *range* of T is possible. As indicated above, once there is a decision to introduce a change in the input, there will be some amount of time before the change can be completely realized, which will impact subsequent decisions about the process.

Example 3: As an incentive to use their web site for direct ordering from the manufacturer, HomeWindows promises on-line customers delivery within one week. Suppose, however, that an order is received to make 100 window blinds of Product C, but Product A was currently in production. Operationally, this means a change in the input material from polystyrene (PS) to high-density polyethylene (HDPE). FIGURE 4 shows shrinkage performance for the last 10 units of Product A and the first 25 units of Product C (i.e., the transition started after the tenth unit). The target shrinkage level for new product is 0.047, which is not achieved until approximately 15 units after the change. Combining

Equations (2) - (4) using appropriate parameters gives a mathematical model for the transition trajectory shown in the figure (see Nembhard (1998) for details).

With this type of representation, we can begin to establish expectations about the length of the transition period, T, for the various production changes to the system. In fact, many savvy operators and line managers already have a "sense" of what this is based on their experience (Nembhard and Nembhard (2000)). Furthermore, they may know that Product C has a shorter transition if sequenced after Product B than after Product A. This essentially presents the manager with an "option" to delay the change for a possibly more opportune time if there is some flexibility in the production schedule. Quantifying that $T = 8$ hours (for example) is one step in calculating the real option value given by Equation 1.

This information allows us to address questions related to the worth of the change. Given a valuation, we may or may not pass on any additional cost to the customer, but we would have an internal yardstick that recognizes the value of flexibility. It may also suggest a delivery time quote that would coincide with an existing production schedule that would give customers the opportunity to enjoy a lower price. In any event, it provides a mechanism for evaluating the cost of the proposed e-commerce strategy from a manufacturing systems viewpoint.

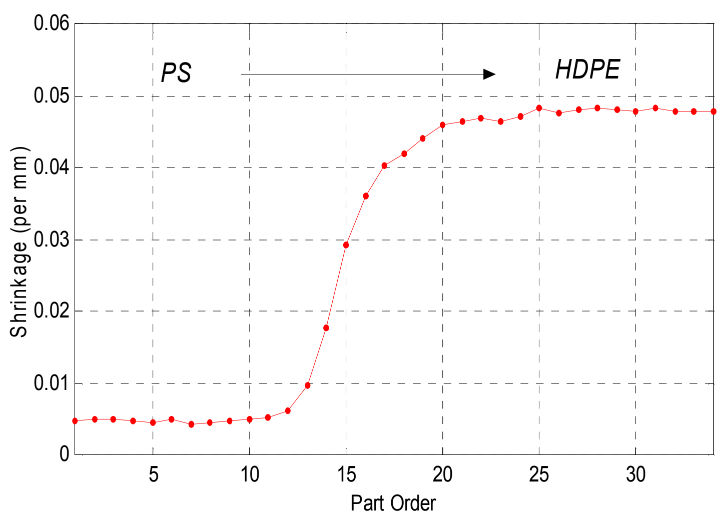

FIGURE 4: A production change requires a material transition from PS to HDPE.

The fourth issue is to determine more practical ways of computing real-options value depending upon the nature of the change problem. There are three main types of option calculators for this computation: (1) Black-Scholes option model; (2) Binomial option model; and (3) Monte Carlo simulation (see Figure 3). The first two methods are based on the concept of risk-free arbitrage in the financial market place. The Monte Carlo simulation approach is often used for valuation options when assumptions of simpler analytical models are violated. One type of option valuation model stand out in terms of practical implementation for a given transition problem.

The Black-Scholes Option Model:

The model (Black and Scholes (1973)) is based on the assumption that the stock price S_t follows the dynamics given by the stochastic differential equation

$$\mathrm{d}S_t = \mu S_t \mathrm{d}t + \sigma S_t \mathrm{d}N_t$$

where $\mathrm{d}Z_t$ is the standard Wiener process whose increments are uncorrelated and μ and σ^2 are the annualized drift and variance rate of the underlying stock, respectively. Risk-neutral valuation (e.g., Cox and Ross (1976) and Harrison and Pliska (1981)) justifies $\mu = r_f$, and the general solution of this differential equation is given by Ito's equation, which yield a lognormally distributed random variable

$$S_t = S_0 e^{[(r_f - \sigma^2/2)t + \sigma N\sqrt{t}]}$$

where S_0 is the initial stock asset, N is distributed as a normal random variable with mean 0 and standard deviation 1 ($N \sim \text{Normal}(0,1)$).

Although it is usually impossible to find an analytical solution to the Black-Scholes equation, it is possible to find such a solution for a European call option. Consider a European call option with the variables given in TABLE 1. The Black-Scholes solution is defined by

$$C(S_t) = S\,N(d_1) - X\,e^{-r\,(T-t)}\,N(d_2) \qquad (5)$$

where

$$d_1 = [\ln (S / X) + (r + \sigma^2 / 2)(T - t)] / [\sigma \ (T - t)^{1/2}]$$

$$d_2 = [\ln (S / X) + (r - \sigma^2 / 2) (T - t)] / [\sigma (T - t)^{1/2}] = d_1 - \sigma (T - t)^{1/2}$$

This formula states that the value of the call option is equal to a fraction of the stock's current price minus a fraction of the exercise price.

Example 4. Customer feedback collected via the HomeWindows intranet revealed a demand for a new window product type that has a lighter fabric (see FIGURE 2). This new product, Product D, will be sold for $100 each. The initial demand for Product D is 1,000 units/month but that demand has a standard deviation of $\sigma = 0.33$. The product will be introduced over a four month period ($T = 4$). The monthly interest rate is constant at 1% ($r = 1.01$). Suppose we let $S = X =$ $100*1,000 = $100,000. (Note the equivalent interpretations for these parameters in Table 1). With these parameters, the Black-Scholes equation (5) gives an option value at time zero of $8,155.

With this type of approach, managers can get a better handle on the value of flexibility within a setting that may require more sequential decision making. For instance, if they realized that S or K changed during the transition to the new product due to higher R&D costs, more operational action, higher labor costs, etc., the Black-Scholes model - and the decision to go forward with the new product - can be re-evaluated (just as financial options can be re-evaluated or even sold after purchase).

Several extensions to the Black-Scholes equation have relaxed some of the assumptions in the original solution and have accounted for the specific features of the underlying asset in various financial options. Extensions that are particularly relevant for real options include cases where the underlying asset has leakage (noise changes) and its value follows lognormal diffusion process with random jumps (Amram and Kulatilaka (1999)). The following scenario (Kumar (1999)) is an example of a more complex problem where the Black-Scholes model would be suitable: Manufacturing plants often need to decide whether and how to alter production in response to changing demand. Assume that the demand (revenue) for a product is increasing at a certain rate (with some fluctuation that is normally distributed over small time intervals). Also assume that the cost of production increases over time at a certain rate. At the same time, the value of the option to alter the production quantity depends on the actions of competitors. Competitive action (such as increase in production) is described by a distribution and has the effect of decreasing revenue. It is assumed that the organization that invests early cannot preempt investment by competitors. This allows us to determine the value of an option to invest an expected amount.

The Binomial Option Model:
The binomial option valuation model is based on a simple representation of the evolution of the value of the underlying asset (Cox, Ross, and Rubinstein (1979) and Cox and Rubinstein (1985)). In each period, the underlying asset can take only one of two possible values. For example, the asset has an initial value, S, and within a short time period either moves up to *uS* or down to *dS*, thus creating a lattice. The binomial option valuation formula for a one-period call option on an asset governed by a binomial lattice is

$$C = \frac{1}{r}\left[qC_u + (1-q)C_d\right] \qquad (6)$$

where the value of moving up C_u = max ($uS - X$, 0), the value of moving down C_d = max ($uS - X$, 0), and the risk-neutral probability $q = (r - d) / (u - d)$. The valuation for multi-period options simply uses Equation (6) multiple times, working backward one period at a time as done in Example 5.

The distribution of outcomes becomes smoother as the number of asset changes per year increases. As the number of asset changes increases (say, weekly), the Binomial option model will produce the results similar to those obtained with the Black-Scholes model. In fact, the Binomial approach provides a good analytical approximation for the movement of the stochastic variable when exact formulas for the stochastic process are not readily available. Of course, the lattice approach can be extended to consider more alternatives in each time period (e.g., Boyle (1988) develops a pentanomial lattice).

Example 5: Suppose HomeWindows wants to introduce two new products, Product E and Product F. Both products will be sold at a price of $100 each and both have a current demand of 1,000 units/month. Product E has a constant demand. However, Product F has a fluctuating demand with an equal probability of increasing 10% (let u = 1.10) or decreasing 10% (let d = 0.90). The monthly interest rate is constant at 1% (let r = 1.01). This implies a risk neutral probability q = 0.55. The setup cost for changing production from one product to the other is $1,000.

Based on this scenario, we can develop a four-month production plan using a binomial option model. The binomial lattice for the demand of Product F is given in FIGURE 5. Assuming that HomeWindows is currently producing Product E, the decision to switch to make Product F will only occur when its demand is greater than 990 units (the manufacturer can make \$100,000 - \$1,000 = \$99,000 when they transition to Product F). If demand for Product F is less than 990 units month, HomeWindows will produce Product E.

FIGURE 6 shows the dollar value of production for four months. The decision to make Product E is shown in plain type; the decision to make Product F is in bold type. The values in the lattice are determined from the product of the price and the demand of the product actually made.

FIGURE 7 shows the option value during the four-month horizon. The final node values are determined from the expiration values of the call, which is the maximum of 0 and S - X. For example the top node for month four is \$133,100 - \$100,000 = \$33,100. Working backward one period at a time, the previous nodes are found using Equation (6). As an illustration, the discounted expected value at the top node for month 3 is [q*(\$33,100) + (1-q) * (\$8,900)] / r = \$21,990.

The NPV of the option, given by the origin node, is \$8,872. Notice that this value is a result of holding the option to change the production between the two product types.

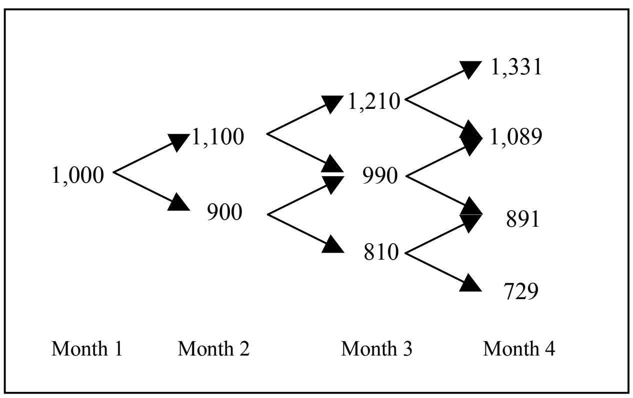

FIGURE 5. Binomial lattice for the monthly demand of Product F.

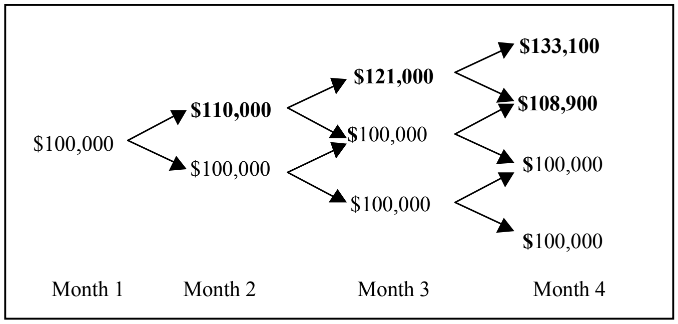

FIGURE 6: Dollar value of production. (Plain type indicates Product E; **bold** type indicates Product F.)

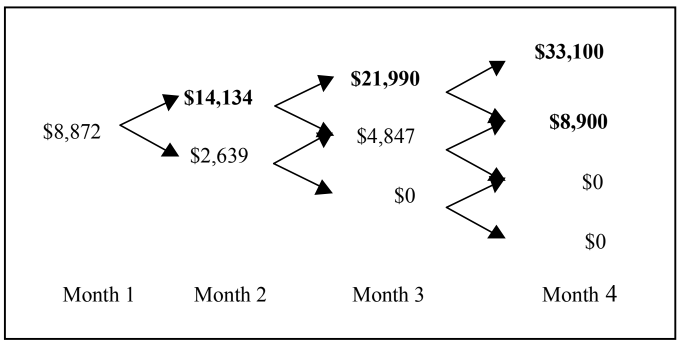

FIGURE 7. Option value. (Plain type indicates Product E; **bold** type indicates Product F.)

Monte Carlo Simulation:

Due to the complexity of the underlying dynamics, analytical models for option valuation entail many restrictive assumptions. That is, exact "easy" expressions for the option valuation are only obtainable if all parameter values are known (e.g., for the Black-Scholes model). This difficulty necessitates the use of an approximate numerical method such as Monte Carlo simulation. Boyle (1977) was among the first to propose using Monte Carlo simulation to study option valuation. Since then many researchers have employed Monte Carlo simulation for analyzing options markets (Figlewski (1989), Hull and White (1987), Johnson and Shanno (1987), Scott (1987), and Fu and Hu (1995)).

The advantage of the approach is its generality in being able to model "imperfect" market conditions not easily captured in analytically tractable models. As Boyle (1977) stated, "The Monte Carlo method should prove most valuable in situations where it is difficult if not impossible to proceed using a more accurate approach." There is a need for investigating issues related to efficiently estimating various option models via Monte Carlo simulation and including control variates, perturbation analysis, and sensitivity analysis as well as Quasi-Monte Carlo simulation approaches. Work done by Boyle (1977), Ho and Cao (1991), Fu and Hu (1995), and Birge (1994) address this topic.

Example 6*:* We illustrate the application of Monte Carlo simulation using the scenario in Example 4. To simulate the path followed by the state Variable *S*, we divide the life of the variable into four intervals as we did in the binomial lattice approach. If Δt is the length of one interval, then the relation between the *S* values is given by

$$S(t+\Delta t) = S(t)e^{(r-\sigma^2/2)}\Delta t + \sigma N\sqrt{\Delta t}$$

Conducting 1,000 Monte Carlo runs of this equation gives an option value of \$8,203. This can be compared to the value of \$8,155 obtained using the Black-Scholes method.

Of course, simulation is unnecessary for a basic valuation when the Black-Scholes model provides a better method. However, the same approach is used for evaluating other types of options or larger lattices. Nembhard, Shi, and Aktan (2000) use Monte Carlo simulation to evaluate a series of European options for a pentanomial lattice associated with applying a statistical process control chart to monitor quality.

DEVELOPING A GENERAL MODEL FOR FINDING OPTIMAL OPTION VALUES

The fifth issue is to develop a general model for optimizing real option valuation. Often, many decision variables exist in a given option model. For example, consider the European option discussed in TABLE 1. Let the decision variables be the exercise price, *X*, the time to expiration, *T*, and the interest rate, r_f. Then from Equation (1) the NPV, J_T, is a random variable and is a function of θ, where $\theta \in \Theta$ and $\Theta = (X, T, r_f)$. In this case, the following optimization problem arises to find the maximum expected NPV for the option:

$$\max_{\theta \in \Theta} E[J_T(\theta)] = e^{-r_f T}\int_X^{\infty}(x-X)dF_{S_T}(x) \tag{8}$$

These decision variables may represent a large solution space and may be discrete or continuous or mix of both. They have lower and upper bounds, i.e.,

$$L_X \le X \le U_X, \mathrm{L}_\mathrm{T} \le T \le U_T, \mathrm{L}_\mathrm{r} \le r_f \le U_r$$

To develop the full-scale real option models for manufacturing based on the other components of our framework (in FIGURE 3), prior research that may guide our formulation for global optimization includes stochastic programming methods (Birge (1994)) and the nested partitions method (Shi and Ólafsson (2000)). Execution will depend on an understanding of the implementation issues of the optimization procedures – such as efficient search heuristics and sample-path based techniques – for different option models. Work done by Robinson (1996) and Shapiro (1996)) may prove useful in this regard.

CONCLUSIONS

In this paper, we have focused on presenting a framework for manufacturing system changes that will improve operational decision-making. We recognize that more decision-making and operational action at different points in time are required during transitions than in steady state. A model that takes this into account along with issues of flexibility and economic factors could significantly enhance how companies view manufacturing strategy.

This work brings the state-of-the-art financial-option research to the area of managing manufacturing system changes. Certainly additional research development is needed on full-scale models based on the examples given here. There is also much to be done to more fully develop the connection between e-commerce data-mining and specific manufacturing activities. However, we show that the benefits of pursuing this investigation will include an understanding of the impact of e-commerce (or purely commerce) strategies that require manufacturing system changes, an understanding of extending or collapsing the time it takes to implement changes, and an economic analysis of manufacturing operational aspects that have previously been done only through guesswork.

The key to application of this research will be to develop a decision support tool that allows business people to evaluate various manufacturing system change issues via computer. The discussion of this research area thus far has focused on how to quantify, model, and value transitions in manufacturing. This line of investigation will have a significant impact by combining these aspects together to benefit decision making in the business environment. One possibility is to construct an interactive software format. The underlying program for could incorporate the characterization of the manufacturing system change, determine the required parametric values, run the optimization procedures and evaluate the real option. Then, it could construct a decision chart as demonstrated in FIGURE 8 that tells when the option value of the transition is sufficient to exercise the option, i.e., make the system change. This would be an extremely valuable business tool to support better-informed operational decisions.

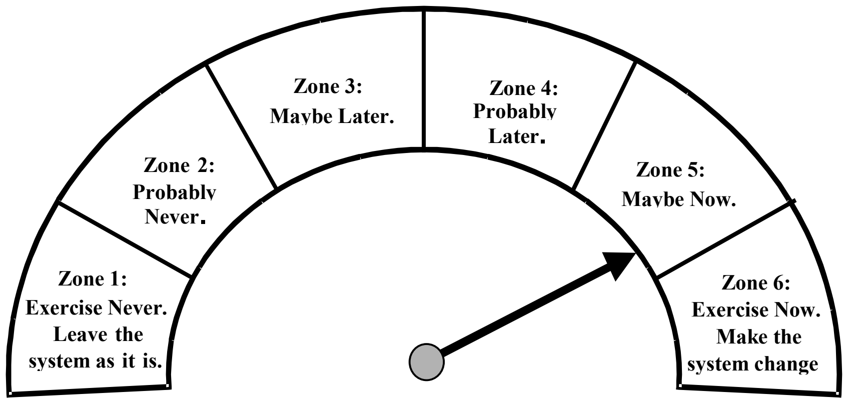

FIGURE 8: Decision chart resulting from the interactive support tool for applying the real option framework. Each zone suggest the course of action for a potential manufacturing system change based on the valuation of the underlying real option.

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ENDNOTES

[1] This case is based on an actual industry company. However, for confidentiality we have changed identifying information.

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