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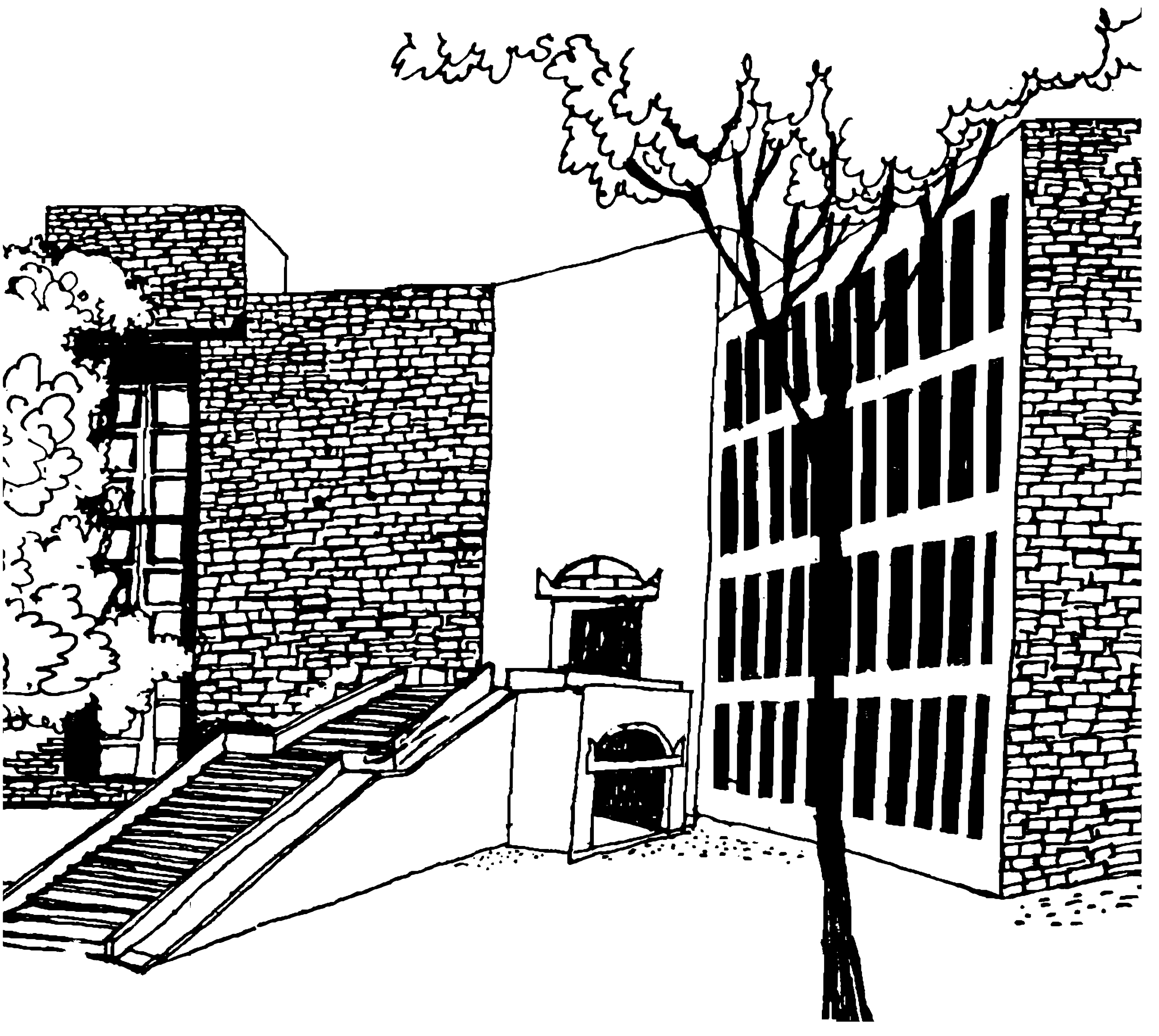

A SCENARIO BASED STOCHASTIC PROGRAMMING APPROACH FOR TECHNOLOGY AND CAPACITY PLANNING

By

Zhi-Long Chen
Shanling Li
&
Devanath Tirupati

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INDIAN INSTITUTE OF MANAGEMENT
AHMEDABAD - 380 015
INDIA

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Zhi-Long Chen
Department of Systems Engineering
University of Pennsylvania
Philadelphia, PA 19104-6315 USA
Email: zlchcn@scas.upcnn.cdu

Shanling Li
Faculty of Management
McGill University
Montreal, PQ Canada, H3A 1G5
Email: li@managcmcnt.mcgill.ca

Devanath Tirupati
P&QM Area
Indian Institute of Management
Vastrapur, Ahmedabad, India 380 015
Email: devanath@iimahd.ernet.in

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Abstract: In response to market pressures resulting in increased competition, product proliferation and greater customization, firms in many industries have adopted modern technologies to provide operational flexibility on several dimensions. In this paper, we consider the role of product mix flexibility, defined as the ability to produce a variety of products, in an environment characterized by multiple products, uncertainty in product life cycles and dynamic demands. Using a scenario based approach for capturing the evolution of demand, we develop a stochastic programming model for determining technology choices and capacity plans. Since the resulting model is likely to be large and may not be easy to solve with standard software packages, we develop a solution procedure based on augmented Lagrangian method and restricted simplicial decomposition. The scope of our approach for deriving context specific managerial insights is illustrated by the results of limited computations. Finally, we demonstrate the versatility of our approach by deriving a special case of the general model to address some tactical issues related to new product introduction.

Key Words: Stochastic Dynamic Demands, Flexible Technology, Capacity and Technology Planning, Scenario-Based Approach, Large-Scale Stochastic Programming

1 Introduction

The decade of the 90s has witnessed an increasingly competitive market place characterized by short product life cycles, demand uncertainty, product proliferation, increased customization, and quick response. A number of companies in diverse industries such as semiconductors and electronics, pharmaceuticals, automotive and fabrication have adopted manufacturing flexibility as a key element of their strategy to cope with this dynamic environment and compete on several dimensions. Typically, advanced technologies such as Flexible Manufacturing Systems (FMS), Computer Integrated Manufacturing (CIM) provide a variety of flexibilities that include volume, routing, process and product mix flexibility. However, these modern technologies are expensive, require significant investments and / or involve higher operating costs in comparison with dedicated facilities designed to produce efficiently a limited set of products. The trade-offs involved in the acquisition of these modern technologies are conceptually well understood. However, limitations of evaluation methodologies and justification techniques have been well documented (see, e.g. Kaplan 1986) suggesting the need for development of economic rationale for such investments. As a result, in recent years there is a growing body of literature on modeling and quantifying the benefits of flexible technologies.

In this paper, we focus on the role of product mix flexibility in an environment characterized by multiple products and uncertainty in product life cycle (PLC) demands. Using a scenario approach to capture dynamic demands and uncertainty associated with PLCs, we develop a stochastic programming model for strategic decisions related to long term technology and capacity planning. The model is quite general and captures a number of issues that include the following: (i) stochastic and dynamic demands, (ii) technology mix between dedicated and flexible technologies, (iii) economies of scope and (iv) economies of scale. Since the resulting stochastic program is likely to be large and not easy to solve with standard packages (even with linear costs), we present solution procedures to facilitate implementation of the approach. Our algorithm, based on augmented Lagrangian method and restricted simplicial decomposition, can provide optimal solutions for moderate sized problems with linear costs (few thousand scenarios) in reasonable time. Using computational results we demonstrate the application of our approach for obtaining managerial insights into issues related to technology and capacity planning.

It is interesting to note that the general model developed in this paper simplifies readily for certain special cases which may be used to address some tactical problems that arise in this context. We discuss in detail one such application dealing with new product introductions and illustrate the tactical model with a case from the pharmaceutical industry (Pisano and Rossi 1994).

The remainder of the paper is organized as follows. In the following section, we present an overview of the related literature. Section 3 is devoted to the development of the general model and the solution procedure. The tactical model for evaluating product introductions is considered in Section 4. We describe computational experiments and the resulting insights in Section 5 and conclude in Section 6 with some remarks on the scope of the model.

2 Literature Review

The literature related to flexibility, technology choice and capacity planning is quite diverse and comes from a variety of disciplines such as Management Science, Operations Research, Operations Management, Economics etc. and a comprehensive review is beyond the scope of this paper. Instead, we provide a brief overview of research dealing with technology and capacity choices in the context of uncertain demands. In contrast to the extensive literature on the general subject of flexibility, reported work in our focused area is fairly recent and quite sparse. Topic-specific review papers, emphasizing different aspects, include the following: Finnie (1988), Swamidass and Waller (1990) on the role and merits of financial appraisal decisions to acquire advanced manufacturing technology; Fine (1993) on models for new technology choice and adoption; Mahajan and Wind (1986) and Mahajan et al. (1990) on diffusion of innovations; Sethi and Sethi (1990) on flexibility in manufacturing; Pierskella and Voelker (1976) on equipment replacement models; and Li and Tirupati (1992) on capacity expansion and planning.

In modeling demand uncertainty and considering capacity and technology choices, it is useful to distinguish between two factors that contribute to this uncertainty. The first is a random (or noise) component, usually modeled as an additive or multiplicative term to complement a predictable demand pattern that could incorporate dynamic factors such as seasonality, trend, cyclicity etc. The second factors relates to the uncertainty associated with the demand pattern, typically used to describe the evolution of demand over the product life cycle and / or the planning horizon. The primary characteristic that distinguishes the two factors is the behavior of uncertainty over time. In the first approach, the random components are permitted to be dynamic (i.e., vary with time) but assumed to be mutually independent. As a result, the demand history does not provide any additional information about future demand. Coupled with an appropriate predictable component, such models could be used to describe a variety of stochastic dynamic demands. In contrast, in the second approach, the focus is on capturing demand dependencies over time and the associated uncertainties. Such dependencies could arise, for example, when the demand is strongly influenced by the degree of product success. Thus, demand for successful products could be consistently high in successive periods. For ease of exposition we refer to the two approaches as stochastic demand and life cycle uncertainty approaches. Clearly, identifying the sources of uncertainty and their characterization would be useful in developing appropriate strategies for coping with them. However, in practice, both types of variations exist together, and are often not distinguishable, thus making the decision problem more complex.

Much of the reported literature (with one exception discussed later in this section) deals with the first approach and the results and analysis are based on the independence assumption described above. For example, Cohen and Halperin (1986) use a discrete period, finite horizon model to consider the technology choice problem in the context of a single product with dynamic, uncertain demands. Each technology is uncapacitated and characterized by a fixed acquisition and variable operating costs. The focus of the paper is on identifying conditions for switching technologies. The authors discuss extensions to consider capacity constraints. Similarly, Fine and Freund (1990) consider the optimal mix between dedicated and flexible technology for a two product situation with static, uncertain demands. Using a scenario approach for describing the potential demand realizations, they formulate the technology - capacity problem as a two stage model. The first stage captures strategic choices and deals with investment decisions in flexible and dedicated technologies. The second stage is operational and focuses on capacity allocations after the demand realizations are known. The second stage decisions could be interpreted as a multiperiod problem with the allocations changed in each period following the demand realizations. The paper develops a number of structural results characterizing the optimal choices in capacity and technology. It may be noted that in the two examples described above the models are profit maximization problems with constraints on demand. Chakravarty (1989) considers a different version of the two product problem in which prices and shortage costs are not specified and examines the role of rationing policies to achieve prespecified service levels in shortage situations. His results demonstrate that such policies do impact capacity choices and hence need to be considered at the strategic level. A key assumption in the literature cited above is linearity in capacity costs that makes the resulting optimization problems tractable and the analyses in the papers provide useful structural results. However, these models ignore economies of scale which are significant in most investment situations.

Another stream of recent literature considers the trade-offs between dedicated and flexible technologies in the presence of scale economies. Since the resulting problems are not tractable most of the insights obtained are based on computational results. For example, Li and Tirupati (1995) consider a two product problem to determine capacity choice to achieve prespecified service levels independent of allocation policies. Their results suggest that often optimal strategy requires a mix of dedicated and flexible facilities. Li and Qiu (1996) obtain similar results while considering operational factors that include setup times. Li and Tirupati (1996) examine the interaction between operating policies and investment strategies in the context of large number of products and suggest procedures to determine robust capacity strategies that perform well under a variety of rationing policies.

It is interesting to note that most of the literature dealing with uncertain demands is based on the stochastic demand approach (the first approach) and does not permit dependencies over time. We believe this is a key feature of the markets in the 90s with increased product proliferation and customization. As a result, the product success is determined in the market place and thus there is a strong correlation between demands over the product life cycle. Hence, our focus in this paper is to develop a modeling approach to determine technology and capacity choices in an environment characterized by life cycle uncertainty (the second approach). Eppen et al. (1989) describe a similar approach to capacity planning using scenarios to describe potential demand price combinations. The planning problem is modeled as a stochastic mixed integer linear program with recourse and is used to examine the trade-offs between risk and returns associated with investments in capacity. While there are similarities between our approach and that of Eppen et al. (1989), in this paper we present a more general model and consider many issues not considered in the earlier work. These include the following: (a) As mentioned earlier, we permit dependencies over time. This is an important feature that provides additional information about future demand and allows dynamic decision making. (b) The number of scenarios considered in Eppen et al. (1989) is small (243, for a five period model). While this was appropriate for the application described in that paper, their solution procedures are limited to small and moderate problems. We develop procedures that can handle much larger problems (up to a few thousand scenarios) suitable for situations with multiple products and / or time periods. We conclude this section by noting that the overview presented in this section has a rather limited scope with focus on the literature relevant to the work reported in this paper.

3 A General Model with Stochastic Dynamic Demands

In this section we present a general model that considers multiple products with dynamic, uncertain demands and technology alternatives characterized by economies of scale and scope. The objective is to determine optimal investments in technology and capacity plans over a multiperiod planning horizon. Similar to Fine and Freund (1990), the model also determines tactical decisions related to allocations of flexible capacity as a function of demand realizations and capacity plans. We consider the above issues faced by a firm producing multiple products and examine the role of product mix flexibility. For ease of presentation we assume that only two types of technologies are available – (a) dedicated, designed to produce efficiently one product and (b) flexible, capable of producing all products. We note that the model can be modified easily to incorporate other types of technologies providing partial flexibility in terms of producing a subset of products. (This extension is mentioned briefly in Section 6.) As noted earlier, these issues are becoming important for firms in several industries facing product proliferation and short product life cycles, and significant investments for capacity additions. Examples of such firms can be found in semiconductor (Texas Instruments), pharmaceuticals (Eli Lilly), and automobile (General Motor, Ford) industries. We use a scenario approach for modeling demand uncertainty. This approach is similar to the ones used by Fine and Freund (1990) and Eppen et al. (1989) and is based on the premise that potential demand outcomes in any period may be specified as discrete alternatives. This assumption is consistent with the practices of many firms whose demand forecasts for medium and long term are conditional estimates based on states of nature. The latter could include firm specific factors (for example, chances of product success) and global factors such as GNP, level of economic activity etc. Often, such forecasts are in the form of optimistic, most likely and pessimistic estimates and fit our model quite well. When there are dependencies over time, a tree structure may be used to capture the evolution of demand over the planning horizon. Figure 1 describes such a tree for a two product example with a three period horizon. As shown in the figure, the number of demand outcomes are two in each of the first two periods and three in the third period. Each arc in the tree represents one set of demand (one for each product) outcomes in a period and a path from the root node to a node in period t describes one possible demand evolution till period t. In our model, each scenario defines a set of possible outcomes over the planning horizon – demand realizations for each product in each period. Clearly, a path from the root node to a terminal node represents a scenario. Further, there is a one to one correspondence between scenarios and paths from the root node to a terminal node in the tree structure. It may be noted that while no two scenarios are identical, partial sharing of demand history between scenarios is inevitable. In the formulation presented below we assume that capacity decisions in each period are made before demands for the period are observed and capacity allocations are made after demands are realized. These assumptions are not critical, and may be modified without seriously affecting the model structure or the results of our paper.

3.1 Notation and Model

We introduce the following definitions and notation:

- N = the total number of products, indexed as $1, 2, ..., N$.
- $N+1$ = the number of technology types, indexed as $0, 1, ..., N$, where 0 represents the flexible technology and i $(1 \leq i \leq N)$ the i-th dedicated technology.
- T = the planning horizon, indexed as $1, 2, ..., T$.
- S = the total number of scenarios for demands, indexed as $1, 2, ..., S$;
- $\mathcal{A}(t)$ = the set of arcs in the scenario tree in period t, for $t = 1, 2, ..., T$.
- $\mathcal{N}(t)$ = the set of nodes in the scenario tree at the beginning of period t, for $t = 1, 2, ..., T$.
- Γ_t^α = the set of scenarios that share a common arc α in the scenario tree in the period t, for $\alpha \in \mathcal{A}(t)$; and $t = 1, 2, ..., T$.
- Γ_t^β = the set of scenarios that share a common node β in the scenario tree at the beginning of period t, for $\beta \in \mathcal{N}(t)$; and $t = 1, 2, ..., T$.
- P_s = the probability that scenario s occurs.
- D_{it}^s = the demand of product i in period t under scenario s, for $i = 1, 2, ..., N$; $t = 1, 2, ..., T$; and $s = 1, 2, ..., S$.
- C_{i0} = the initial amount of capacity of technology type i at the beginning of period 1, for $i = 0, 1, ..., N$.
- X_{it}^s = the amount of capacity addition for technology type i at the beginning of period t under scenario s, for $i = 0, 1, ..., N$; $t = 1, 2, ..., T$; and $s = 1, 2, ..., S$.

- Y_{it}^s = the amount of dedicated technology type i allocated to product i in period t under scenario s, for $i = 1, 2, ..., N$; $t = 1, 2, ..., T$; and $s = 1, 2, ..., S$.

- Z_{it}^s = the amount of flexible capacity allocated to product i in period t under scenario s, for $i = 1, 2, ..., N$; $t = 1, 2, ..., T$; and $s = 1, 2, ..., S$.

- I_{io} = the initial inventory of product i at the beginning of period 1, for $i = 1, 2, ..., N$.

- I_{it}^s = the amount of inventory of product i at the end of time period t under scenario s, for $i = 1, 2, ..., N$; $t = 1, 2, ..., T$; and $s = 1, 2, ..., S$.

- $F_{it}(\cdot)$ = the investment cost function for technology i in period t, for $i = 0, 1, ..., N$; and $t = 1, 2, ..., T$.

- U_{it} = the unit operating cost for product i by dedicated technology in period t, for $i = 1, ..., N$; and $t = 1, 2, ..., T$.

- V_{it} = the unit operating cost for product i by flexible technology in period t, for $i = 1, ..., N$; and $t = 1, 2, ..., T$.

- H_{it} = the unit holding cost for product i in period t, for $i = 1, ..., N$; and $t = 1, 2, ..., T$.

We now present the general model (GM) as below:

[GM]:

$$\min_{X,Y,Z,I} \quad \sum_{s=1}^{S} P_s \left\{ \left[\sum_{i=0}^{N} \sum_{t=1}^{T} F_{it}\left(X_{it}^s\right) \right] + \left[\sum_{i=1}^{N} \sum_{t=1}^{T} \left(U_{it} Y_{it}^s + V_{it} Z_{it}^s\right) \right] + \left[\sum_{i=1}^{N} \sum_{t=1}^{T} H_{it} I_{it}^s \right] \right\} \tag{1}$$

subject to

$$Y_{it}^s \leq C_{i0} + \sum_{\tau=1}^{t} X_{i\tau}^s \quad i = 1, ..., N; \; t = 1, ..., T; \; s = 1, ..., S \tag{2}$$

$$\sum_{i=1}^{N} Z_{it}^s \leq C_{00} + \sum_{\tau=1}^{t} X_{0\tau}^s \quad t = 1, ..., T; \; s = 1, ..., S \tag{3}$$

$$B_{i0} + Y_{i1}^s + Z_{i1}^s = D_{i1}^s + I_{i1}^s \quad i = 1, ..., N; \; s = 1, ..., S \tag{4}$$

$$I_{i,t-1}^s + Y_{it}^s + Z_{it}^s = D_{it}^s + I_{it}^s \quad i = 1, ..., N; \; t = 2, ..., T; \; s = 1, ..., S \tag{5}$$

$$X_{it}^u = X_{it}^v \quad u, v \in \Gamma_t^{\beta}; \; \beta \in \mathcal{N}(t); \; t = 1, ..., T; \; i = 0, ..., N \tag{6}$$

$$Y_{it}^u = Y_{it}^v \quad u, v \in \Gamma_t^{\alpha}; \; \alpha \in \mathcal{A}(t); \; t = 1, ..., T; \; i = 1, ..., N \tag{7}$$

$$Z_{it}^u = Z_{it}^v \quad u, v \in \Gamma_t^{\alpha}; \; \alpha \in \mathcal{A}(t); \; t = 1, ..., T; \; i = 1, ..., N \tag{8}$$

$$X_{it}^s \geq 0, \quad Y_{it}^s \geq 0, \quad Z_{it}^s \geq 0, \quad I_{it}^s \geq 0 \qquad t = 1, ..., T; \; i = 0, ..., N; \; s = 1, ..., S \tag{9}$$

The objective function (1) minimizes the total of investment and operational costs comprising of production and inventory carrying costs over the planning horizon. When demand constraints are soft and it is not essential to meet all demands, the objective function can be modified to include shortage costs. Alternately, the problem can be formulated to maximize profits, given the price function. It may be noted that while the investment cost functions $F_{it}(\cdot)$ are general to permit economies of scale, we assume that operating costs and inventory holding costs are linear with production volume. (2) denotes capacity constraints on dedicated technology while (3) represents constraints on flexible capacity. (4) and (5) specify that demand be satisfied for each product in each period under all scenarios. Finally, (6) – (8) represent logical constraints that require some elaboration. In stochastic programming literature such constraints are referred to as nonanticipativity constraints (for details, see Birge and Louveaux 1997, P. 96). These constraints arise out of the recognition that when two scenarios share demand history till time t, all the decisions till time t must be the same for the two scenarios. In [GM], (6) denotes nonanticipativity constraints on capacity additions. Likewise, (7) and (8) respectively represent the corresponding constraints for allocations of dedicated and flexible capacities. Similar constraints for inventory become redundant as a result and hence omitted in the formulation. We conclude this section with a few comments about the model [GM]. While we have included inventory decisions in the model for the sake of completeness, they may not be very significant in the context of strategic and tactical decisions. Typically, in such situations the periods are fairly large (one year, for example). In such cases, the inventory variables can be set at zero and deleted from the model without affecting its structure. Second, it may by noted that while the formulation of [GM] is straightforward, the problem becomes large fairly quickly because of the exponential growth in the number of scenarios with the number of products and time periods. In the following section we discuss solution procedures to solve the model [GM] with linear investment cost functions.

3.2 An Algorithm for Optimal Solutions

The model GM is a large scale stochastic program with $(4N + 1)ST$ variables and $(2N + 1)ST$ constraints exclusive of the nonanticipativity constraints. Even with linear cost functions, the resulting problems are not easy to solve using standard optimization packages. Hence, in this section we present a computational procedure for deriving optimal solutions for moderate sized problems with linear investment cost functions F_{it}. For [GM] with concave costs and / or larger sized problems, we suggest a heuristic procedure described in Chen et al. (1998), an unpublished, extended version of the present paper.

Before we present the algorithm, we first observe that the model [GM] with linear investment costs has a primal block angular (PBA) format as below:

[PBA]:

$$\text{minimize} \quad \sum_{s=1}^{S} c_s^T x_s \tag{10}$$

subject to

$$A_s x_s = b_s \qquad s = 1, 2, ..., S \tag{11}$$

$$\sum_{s=1}^{S} B_s x_s = d \tag{12}$$

$$x_s \geq 0 \qquad s = 1, 2, ..., S \tag{13}$$

where (11) represents S independent sets of constraints, each corresponding to one scenario, and (12) is the coupling constraints linking all the scenarios. It is easy to show that constraints (2)-(5) in the general model are simplified into (11) and the nonanticipativity constraints in the general model, (6)-(8), are represented by (12) in [PBA].

To solve [PBA], it is known that Dantzig-Wolfe (DW) decomposition (Dantzig and Wolfe 1960) is a popular solution approach. Unfortunately, in our model, the nonanticipativity constraints (12) link almost all variables. As a result, the number of rows in the DW master problem could be extremely large and makes the DW decomposition impractical.

We propose to use the augmented Lagrangian method (see, e.g. Bertsekas 1982) to solve the problem [PBA]. The augmented Lagrangian function for the problem [PBA] is as follows:

$$L(x, \pi, \rho) = \sum_{s=1}^{S} c_s^T x_s + \pi^T \left(d - \sum_{s=1}^{S} B_s x_s \right) + \frac{1}{2} \rho || d - \sum_{s=1}^{S} B_s x_s ||^2 \tag{14}$$

where π is a Lagrangian multiplier and ρ is a penalty parameter.

The augmented Lagrangian method for solving the problem [PBA] can be described as follows:

Augmented Lagrangian Method (ALM)

Begin with iteration counter $k = 0$.

- **Step 1:** For fixed multiplier π^k and penalty ρ^k, solve the following problem

$$\min_x \quad L(x, \pi^k, \rho^k) \tag{15}$$

subject to

$$A_s x_s = b_s \qquad s = 1, 2, ..., S \tag{16}$$

$$x_s \geq 0 \qquad s = 1, 2, ..., S \tag{17}$$

Let $x^k = (x_1^k, x_2^k, ..., x_S^k)$ be the solution.

- **Step 2:** If

$$\sum_{s=1}^{S} B_s x_s^k = d \tag{18}$$

then stop; otherwise update the multipliers and the penalty parameter:

$$\pi^{k+1} \;=\; \pi^k + \rho(d - \sum_{s=1}^{S} B_s x_s^k) \tag{19}$$

$$\rho^{k+1} \;=\; \gamma \rho^k \tag{20}$$

where γ is a parameter typically selected from the interval $[4, 10]$ (see, e.g. Bertsekas 1982). Increase k by 1 and go to Step 1.

The advantages of the augmented Lagrangian method over traditional dual methods are the simplicity and the stability of multiplier iterations and the possibility of starting from arbitrary π^0 (see Bertsekas 1982 for details). This method has been proven successful in the literature (see, e.g. Mulvey and Ruszczynski 1992, and Bai et al. 1994) for solving large-scale stochastic programming problems with a primal block angular structure. However, an obvious drawback is that the augmented Lagrangian function (14) is not separable although its feasible region is separable. To overcome this drawback, we propose to use the restricted simplicial decomposition (RSD) method (see Hearn et al. 1985 for details) to solve the problem in Step 1, i.e., the problem (15)-(17). RSD is a more sophisticated version of the simplicial decomposition (SD) (Hohenbalken 1977) and designed to solve convex programming problems with linear constraints more efficiently than SD. The core idea of RSD and SD is to find the optimal solution for a nonlinear problem by solving a series of linear problems.

Applying RSD to the problem (15)-(17), we will have a linear problem in each iteration which is separable by scenarios and hence can be solved easily. The details of RSD for the problem (15)-(17) are described as follows:

Restricted Simplicial Decomposition (RSD)

- **Define:**
  - $X_s = \{x_s \geq 0 \mid A_s x_s = b_s\}$, the polytope of block s (here we assume the set X_s is bounded).
  - Ω_s = a set of retained vertices of polytope X_s.
  - Ψ_s = a set that is either empty or contains one of the iterates.
  - $\mathcal{H}(\Phi) = \left\{x = \sum_{x_i \in \Phi} \lambda_i x_i \mid \sum_{x_i \in \Phi} \lambda_i = 1, \lambda_i \geq 0\right\}$, the convex hull generated by the points in set Φ.
  - r_s = maximum number of retained vertices for polytope X_s.

- **Step 0:** Initialization. Set iteration counter $i = 0$.

  Let x_s^0, $s = 1, 2, ..., S$, be a feasible solution in X_s.

  Set $\Omega_s = \emptyset$, $\Phi_s = \Psi_s = \{x_s^0\}$.

- **Step 1:** Auxiliary problem. For each scenario $s = 1, 2, ..., S$, solve the subproblem:

$$\min_{x_s \in X_s} \left(\nabla_s L(x^i, \pi^k, \rho^k)\right)^T \left(x_s - x_s^i\right) \tag{21}$$

  where $\nabla_s L(x^i, \pi^k, \rho^k)$ is the portion of $\nabla L(x^i, \pi^k, \rho^k)$ associated with scenario s and $\nabla L(x^i, \pi^k, \rho^k)$ is the gradient of the objective function (15) at the given point $x^i = (x_1^i, ..., x_S^i)$. Hence

$$\left(\nabla L(x^i, \pi^k, \rho^k)\right)^T \left(x - x^i\right) = \sum_{s=1}^{S} \left(\nabla_s L(x^i, \pi^k, \rho^k)\right)^T \left(x_s - x_s^i\right)$$

  is the linear approximation of the objective function (15) at the given point x^i. Let $\hat{x}_s^i$ denote the solution of the s-th subproblem (21). Clearly $\hat{x}_s^i$ is a vertex of the polytope X_s.

- **Step 2:** Vertex update. If

$$\left(\nabla_s L(x^i, \pi^k, \rho^k)\right)^T \left(\hat{x}_s^i - x_s^i\right) \geq 0, \quad \text{for all } s = 1, 2, ..., S \tag{22}$$

  then stop, the optimal solution to problem (15)-(17) is x^i. Otherwise,

  – if $|\Omega_s| < r_s$, set $\Omega_s = \Omega_s \bigcup \{\hat{x}_s^i\}$;

  – if $|\Omega_j| = r_s$, let $\hat{x}_s^i$ replace the vertex in Ω_s with the minimum weight in the expression of x_s^i as a convex combination of vertices of Φ_s, and let $\Psi_s = \{x_s^i\}$.

  Set $\Phi_s = \Omega_s \bigcup \Psi_s$.

- **Step 3:** Master problem. Solve problem (15)-(17) over a restricted region, that is,

$$\min\left\{L(x,\pi^k,\rho^k) \mid x_s \in \mathcal{H}(\Phi_s),\quad s=1,2,...,S\right\} \tag{23}$$

Since we can express any point $x_s \in \mathcal{H}(\Phi_s)$ as a convex combination of the vertices in Φ_s, i.e.

$$x_s = \sum_{x_{sh}\in\Phi_s} \lambda_{sh}x_{sh}, \quad \text{for some } \lambda_{sh} \geq 0 \text{ such that } \textstyle\sum_{h=1}^{|\Phi_s|}\lambda_{sh} = 1 \tag{24}$$

problem (23) is thus equivalent to the following problem with λ-variables:

$$\min_{\lambda} L(\lambda,\pi^k,\rho^k) = \sum_{s=1}^{S}\sum_{h=1}^{|\Phi_s|} e_{sh}\lambda_{sh} + \left(\pi^k\right)^T\left(d - \sum_{s=1}^{S}\sum_{h=1}^{|\Phi_s|}\lambda_{sh}g_{sh}\right) + \frac{1}{2}\rho^k \parallel d - \sum_{s=1}^{S}\sum_{h=1}^{|\Phi_s|}\lambda_{sh}g_{sh}\parallel^2 \tag{25}$$

subject to

$$\sum_{h=1}^{|\Phi_s|}\lambda_{sh} = 1, \quad s=1,2,...,S \tag{26}$$

$$\lambda_{sh} \geq 0, \quad h=1,2,...,|\Phi_s|;\ s=1,2,...,S \tag{27}$$

where the constant $e_{sh} = c_s^T x_{sh}$ and the vector $g_{sh} = B_s x_{sh}$, correspond to each vertex $x_{sh} \in \Phi_s$.

Let the solution of problem (25)-(27) be λ^*. Then the solution of problem (23), denoted as $x^{i+1} = \left(x_1^{i+1},...,x_S^{i+1}\right)$, is given by equation (24) with λ replaced by λ^*. Discard all vertices x_{sh} with $\lambda^*_{sh} = 0$ from Ω_s or Ψ_s. Set $i = i+1$ and go to Step 1.

We note that the nonseparable objective function (15) is linearized in Step 1. Thus the resulting auxiliary problem in Step 1 is separable. Also note that the master problem (25)-(27) is a convex quadratic program and has a very simple structure in the constraint matrix. This program can be solved easily as long as the number of blocks S (i.e. the number of rows in this program) and the total number of retained vertices $\sum_{s=1}^{S}|\Phi_s|$ (i.e. the number of variables in this program) are not too large.

In summary, we solve the general model [GM] with linear costs by combining Algorithms ALM and RSD. We use ALM in the outer loop for the update of multipliers and penalty parameter and RSD in the inner loop for solving the problem (15)-(17) with the given multipliers and penalty parameter. The sequence of solutions generated by this solution method converges to an optimal solution because both augmented Lagrangian method and restricted simplicial decomposition are convergent.

4 A Tactical Planning Model for New Product Introduction

As mentioned earlier, the model [GM] is quite general and combines strategic and tactical decisions. Models with such a wide scope are not always necessary (particularly, after the strategic decisions have been made). Hence, our objective in this section is to demonstrate that special cases of [GM] can be used to address some of these tactical issues related to technology and capacity choices. An application in the context of a firm manufacturing seasonal products can be found in Chen et al. (1998). The new product introduction application described in this section is in the context of an innovative firm using flexible technology strategy to develop a number of alternative products for markets with high degree of uncertainty with respect to product success in the market and the resulting variability in demand. We use the well documented case of Eli Lilly (Pisano and Rossi 1994) to make our application concrete. However, the model can be adapted easily to other similar situations.

In summary, the situation at Eli Lilly, as described in the case, is as follows. Typical new product development and life cycle follow three phases of varying lengths. In the first phase small quantities of the product are made for clinical trials. The focus is on time, and not much effort is devoted to process development. Following the clinical trials, the firm starts developing, in parallel, manufacturing process suitable for the specific product. In the second phase, the emphasis is on optimizing the manufacturing process while the product is under lengthy FDA approval and market testing as well. The third phase represents commercial production with efficient manufacturing process. The phases are of unequal length and vary between two to twelve years and the total life cycle for a new product may be as long as fifteen years. The traditional approach at Eli Lilly may be characterized as a dedicated strategy in which manufacturing process development for a new product starts as soon as sufficient information is available. The process is optimized for the new product before mass production gets under way. This approach has two serious drawbacks. First, because of uncertainties associated with FDA approval and product development, there were significant delays in obtaining information necessary for process development. Coupled with the long process development times, this resulted in very long time to market causing significant lost revenues in some cases. Second, the time lags and uncertainties were such that capacity decisions had to be made before product success could be established. Capacity additions required significant amount of capital and had high degree of scale economies. Coupled with the fact that dedicated capacity could not be used for any other product without incurring expensive retrofit, made the traditional strategy very risky. In early 90s faced with a number of pressures – increased competition, pricing pressures, decreasing returns from investments on product development, environmental regulations, need for reduced time to market etc, Eli Lilly considered a flexible facility strategy for reducing the risk associated with manufacturing facilities for new products. Under this strategy, the firm would set up flexible facilities for development of new products and products requiring low volume production. Investments in dedicated capacity would occur only after the product success becomes clear and the demand levels warrant such capacity. While the strategy is attractive in principle, it involved significant costs. For example, flexible capacity was more expensive, typically three times the cost of dedicated technology. Because of time lags involved it was impossible to eliminate all risk and commitment to dedicated capacity had to be made while there was some uncertainty.

In this section, we assume that the company has chosen a flexible strategy and has set up flexible facilities. We develop a special case of [GM] to evaluate the implications of this strategy for new product introduction. Specifically, we consider two questions: (a) whether the company should develop the new product, and (b) if yes, the capacity strategy to be followed. To reflect the situation at Eli Lilly, we assume that dedicated capacity can be added in discrete units (0.25 rigs in Eli Lilly's nomenclature). In contrast, we model flexible capacity as a continuous variable that can be used as needed. This is reasonable, given our assumption about the strategic decision. we assume that the cost coefficient of flexible capacity represent opportunity cost as the facility could be used for other products. Finally, we permit multiple time periods of unequal length and ignore inventory carry over between periods. Again, this is reasonable given the lengths of the time periods in each phase. We now present the new product introduction (NPI) model.

[NPI]

$$\min_{X,Y,Z} \quad \sum_{s=1}^{S} P_s \left\{ \left[\sum_{t=1}^{T} F_t X_t^s \right] + \left[\sum_{t=1}^{T} (U_t Y_t^s + V_t Z_t^s) \right] \right\} \tag{28}$$

subject to

$$Y_t^s \leq \sum_{\tau=1}^{t} X_\tau^s \quad t = 1, ..., T_s; \;\; s = 1, ..., S \tag{29}$$

$$Y_t^s + Z_t^s = D_t^s \quad t = 1, ..., T; \;\; s = 1, ..., S \tag{30}$$

$$X_t^u = X_t^v \quad u, v \in \Gamma_t^\beta; \;\; \beta \in \mathcal{N}(t); \;\; t = 1, ..., T; \tag{31}$$

$$Y_t^u = Y_t^v \quad u, v \in \Gamma_t^\alpha; \;\; \alpha \in \mathcal{A}(t); \;\; t = 1, ..., T; \tag{32}$$

$$Z_t^u = Z_t^v \quad u, v \in \Gamma_t^\alpha; \;\; \alpha \in \mathcal{A}(t); \;\; t = 1, ..., T; \tag{33}$$

$$Y_t^s \geq 0; \quad Z_t^s \geq 0 \qquad t = 1, ..., T; \quad s = 1, ..., S \tag{34}$$

$$X_t^s \geq 0, \text{ integer } t = 1, ..., T; \quad s = 1, ..., S \tag{35}$$

where F_t is the investment cost of purchasing one unit of the dedicated technology in period t and X_t^s is the number of units of the dedicated technology purchased in period t under scenario s. The other notation is similar to the corresponding one in [GM].

The formulation above is similar to [GM], follows directly from the assumptions described and requires little elaboration. Unlike the multi-product model [GM], [NPI] is a single product model. (Hence, for ease of exposition, we have omitted the product subscript i in the formulation above.) This simplification is the result of two assumptions: (a) strategic decisions have already been made and flexible capacity is available, and (b) it is easy to determine the opportunity cost of flexible capacity. In the absence of reliable assessment of the opportunity costs, [NPI] may be formulated as a multi-product model with a constraint on flexible capacity linking the individual products. While we have omitted inventory variables in our application their inclusion does not add complexity to model. On the other hand, discrete choices in dedicated capacity make [NPI] an integer linear program that may be difficult to solve for large problems.

5 Computational Results

In this section we describe the results of computational experiments and discuss their implications for deriving managerial insights into issues related to technology choice in the context of stochastic environment considered in this paper. We recognize that our experiments are not comprehensive enough for conclusions based on rigorous statistical analysis. However, they are extensive and permit some generalizations. In addition, the experiments demonstrate that the algorithm proposed for the model [GM] is effective for solving moderate sized problems.

5.1 Results Based on Model [GM]

We conducted two experiments for the general model [GM]. The first experiment, called *robustness experiment*, was focused on the length of the planning horizon and robustness of the first period decisions to changes in the horizon length. In the second experiment, called *impact experiment*, we examine the nature of optimal technology mix and investment and capacity plans under a wide range of demand conditions and cost parameters. In the robustness experiment, all test problems involve two products and eight time periods. Since our experiments found that inventory decisions have little impact on other decisions, we ignored inventory considerations in this experiment. Each test problem is specified by the cost and demand data, the former comprising of investment and operating costs in each period. In each problem, the cost parameters for dedicated technology were identical for the two products. The unit operating and investment costs of dedicated technology in the first period were set respectively at 100 and 200. The corresponding costs for subsequent periods were determined using a discount factor of 0.9 for each period. For defining the costs of flexible technology, we considered 3 levels of operating costs (at 70%, 100% and 130% of the dedicated technology) and 4 levels of investment costs (at 125%, 150%, 175% and 200% of dedicated technology). See Table 1 for the details of the cost data.

The scenario structure is an important characteristic of the problem and we considered three patterns in which the number of possible demand outcomes ranges between 2 and 9. The total number of scenarios in each problem ranged between 3456 and 4608. The details of the scenario structure are shown in Table 1. In generating the product demands in each period we considered the following two factors: total demand variability (R), and individual demand variability (W). The product demands in a period (say, period $t+1$) were derived from the total demand in the previous period (period t) and using the two parameters, R and W, in the following manner. Let D_t be the total demand in period t. Then the total demand at period $t+1$ is generated as $D_{t+1} = D_t(1+g)r$, where g is the growth rate of the total demand and generated randomly from the interval [0, 0.3] (hence an average of 15% growth each period), and r reflects the variability of total demand and is randomly chosen from $[1-R, 1+R]$. Given the total demand D_{t+1} in period $t+1$, individual product demands, $d_{1,t+1}$ (for product 1) and $d_{2,t+1}$ (for product 2), are generated as follows: $d_{1,t+1} = pD_{t+1}$, and $d_{2,t+1} = D_{t+1} - d_{1,t+1}$, where p is randomly chosen from the interval $[0.5-W, 0.5+W]$. The procedure above is followed for generating the demands in each scenario. In generating the test problems, we considered two levels for each of the variability parameters, R and W. The levels were chosen as 0.2 and 0.4 to obtain a wide variation of demand in our test problems.

In summary, the combination of demand and cost parameters yields 144 data sets. For each data set we generated five test problems in a random manner as described earlier, resulting in a total of 720 problems. For the sake of brevity we do not present the details of the data used in our test problems. (These may be obtained from the authors by the interested readers.) An overview of the design of our test problems for the robustness experiment is presented in Table 1.

In the impact experiment, we examine in detail the impact of cost and demand patterns on technology mix and capacity choices. Again, we considered only two-product problems and ignored inventory considerations. The planning horizon for this experiment was set at 5 periods. This choice was motivated by our observation that, in practice, five-year plans with one-year time periods are quite popular for long-term planning. This choice was also consistent with the results from our robustness experiment (discussed later in this section). The design of this experiment was the same as the robustness experiment described earlier except that only the first 5 periods are considered and the scenario structure was a little more elaborate with number of joint demand outcomes in a period ranging between 2 and 16. The total number of scenarios in a test problem ranged between 2304 and 3456. The three patterns of scenario structures used in the experiment are shown in Table 1. As in the robustness experiment, there are 144 data sets defined by the cost and demand parameters, and for each data set, we generated five test problems, resulting in a total of 720 problems.

Discussion of Results

As mentioned earlier, in the robustness experiment we examine the influence of the length of the planning horizon on the first period investment decisions. Accordingly, for each test problem we generate four subproblems by varying the number of time periods from 5 to 8. Each subproblem is derived by simply truncating the problem at the desired length and dropping all subsequent data. We chose the optimal first-period solution of the 5-period subproblem as the candidate solution for assessing the impact of changing horizon length. This choice was motivated by our observation that, in practice, five-year rolling horizons with yearly periods is quite popular for long-term planning. Accordingly, we determine, for each subproblem, the relative error in the objective function due to the candidate solution with the first-period decisions dictated by the solution of the 5-period subproblem. (The reader may note that this requires solution of each subproblem twice, once to optimality and the second with specified decisions in the first period.) Again, for the sake of brevity, we do not present the detailed solutions. Instead we provide summary results in Table 2. The table presents, for each combination of investment and operating cost parameters, the average and the maximum relative error for all problems in the group. Thus each entry in the table represents a summary of 60 test problems. The relative errors are reported for each subproblem. E_6, E_7, and E_8 represent relative errors for the 6-period, 7-period, and 8-period subproblems respectively. The results in the table are very encouraging and suggest that, from a managerial perspective, the first period solution of the five-year problem is quite robust. For example, the average error is quite small and less than 0.5% for every data set. Even the maximum relative error is less than 1%. Furthermore, about 30% of the test problems yield no error at all in all three subproblems. It is interesting to note that the relative error is not monotone in the length of the planning horizon. While this is not surprising, it is useful to note that increasing the planning period (with implications for generating good forecasts) may not always be helpful.

In the impact experiment we focused on the impact of demand and cost parameters on the optimal mix of technology and capacity plans. Accordingly, we computed the following measures for each test problem: (a) the proportion of flexible capacity added in each period, (b) the ratio of flexible capacity to total capacity in each period, (c) costs of flexible capacity, both investment and operating costs, relative to the total cost. In addition, we compared the cost of the optimal solution with those corresponding to extreme solutions of all-dedicated and all-flexible technology strategies. The relative cost penalties of these extreme strategies provide an indication of the economic consequences due to adoption of such strategies based on faith, without adequate analysis. In our experiments, we did not observe significant differences due to the alternate scenario structures. Hence, we have aggregated these results and report a summary in Tables 3-6. The tables contain, for each set of cost parameters, the average of the measures described above. Each average is over 15 test problems (five for each of the three scenario structures).

Not surprisingly, some of our results are consistent with intuition and agree with earlier studies on this subject. These include the following and require little elaboration:

- For a given level of demand variability (defined by R and W), the amount of flexible capacity increases with reductions in cost of flexible technology.
- Most of the flexible capacity additions occur early in the planning horizon. For example, as can be seen from Tables 3-6, in most cases, the proportion of flexible capacity in the first period is more than 60%. We conjecture that in the presence of scale economies this figure could be even higher.

While the above conclusions are obvious, our results demonstrate clearly the need for a systematic approach based on sound models for making technology and capacity choices. For example, the results in the tables lead to the following conclusions:

- Extreme strategies (either all-dedicated or all-flexible) could lead to severe cost penalties and are as high as 36% in some cases.

- Both extreme strategies fail in at least 50% of the test problems. A strategy resulting in a cost penalty greater than 5% is considered a failed strategy.
- The amount and time of capacity additions depend on a combination of a number of factors related to demand and costs and generalizations based on limited data could be misleading. For example, in our test problems, the amount of flexible capacity as a fraction of total capacity ranged from 0 to 88%. This indicates that such decisions should be resolved based on specifics of a given situation, rather than relying on thumb rules.
- Flexibility is more useful in the presence of individual demand variability (in comparison with total demand variability). For a given set of cost parameters, amount of flexible capacity always increases with a higher value of W. Similar increases occurred when the factor R was increased, but not always. Perhaps this is due to the fact that there are no scale economies in investment and the growth trend in demand. Together these factors favor dedicated technology.

5.2 Results Based on Model [NPI]

The data set for the experiment with the model [NPI] is based on the case presented in Pisano and Rossi (1994) described in Section 4. The investment and operating costs for dedicated technology were taken directly form the case. In the absence of any information on opportunity costs, we used the data on investment and operating cost data to derive the per unit cost of usage of flexible capacity. While each of the first two phases were modeled as one period, the third phase consisted of three periods to represent the growth, maturity and declining stages of the product life cycle. It may be noted that periods are of unequal length and dictated by product life cycle. The base demands presented in the case were used as the initial demands. In both Phases 1 and 2, we assume there are only two possibilities: success and failure. In Phase 3, we assume that there are three outcomes (high, medium and low) in each period. Based on the demand data given in Pisano and Rossi (1994), we grouped them into three phases, and added high and low demand volumes in each period of the third phase. In phase 1, we considered five levels of probability for product success and in phase 2, three levels of probability to reflect the high uncertainty of a new product in its life cycle. Needless to say, failure at any stage makes the demand for the remainder of the planning horizon zero. Table 7 provides a summary of the data used in these test problems.

Discussion of Results

In the experiment, we had 9 problems for each level of product success in the first stage. Thus we had forty five test problems for each product, in all 135 problems. Each problem was directly solved by the commercial optimization software package CPLEX (1995). Our computational results suggested that the effect of uncertainties in the second and third phases were relatively minor. Hence, we only report the average of the measures for the nine problems in each data set defined by the level of product success in phase 1. These results, reported in Tables 8 and 9 include the following: (a) cost implications, relative to all-dedicated and all-flexible strategies (see Table 8), and (b) capacity strategy, defined by the amount of flexible capacity as a fraction of total capacity and the timing of this usage (see Table 9).

Similar to the problem [GM], the results with [NPI] suggest that the cost penalties of extreme strategies can be very severe. The results are quite dramatic and the penalty, in some cases, is more than 200% (product C). Due to low volumes in the case of product C, flexible capacity is more useful and all-flexible strategy is reasonable. The results reinforce the intuition behind use of flexible capacity as a hedge. In all cases, flexible capacity is used in the first two phases with significant uncertainty about product success and low demands. Phase 3 represents the point of departure, and dedicated capacity becomes attractive when the demands are sufficiently high. Again, use of dedicated capacity for product C is limited because of relatively low volumes even when successful. Such facilities are justified only in period four when justified by the level of demand. It may be noted that scale economies are significant for dedicated facilities and investments in them are not attractive for low levels of demand.

We conclude this section with some comments on the computational performance of the algorithm developed for solving [GM] in this paper. The algorithm was implemented using C language and all the computations were carried out on a Sun Ultra workstation. In terms of the computational time, for the test problems we solved with model [GM] (with up to 4608 scenarios), our algorithm clearly outperformed the direct solver that uses CPLEX directly. Our limited experiment on other problems with the same model showed that the direct solver could outperform our algorithm for smaller problems (with fewer than 500 scenarios), but our algorithm is much more effective than the direct solver for larger problems (with more than 1000 scenarios). Our algorithm is capable of solving problems with up to 5000 scenarios in reasonable time. It may also be noted that the direct solver is likely to have memory storage difficulty for large problems with more than

2000 scenarios, which may severely limit its application.

6 Conclusion

In this paper we considered a problem of technology and capacity planning in an environment characterized by multiple products, stochastic demands and technology alternatives distinguished by investment and operating costs. We formulated the decision problem involving strategic and tactical decisions as a stochastic programming model. The strategic decisions relate to technology choice and investments in new capacity. These are long-term decisions often made with imperfect knowledge of demand. Tactical decisions, on the other hand, deal with allocation of capacities among products and are made after demand realizations are known. Our model is based on the use of scenario approach to capture demand uncertainty and its evolution. A key feature of this model is a provision for dependent demands that permit demands in later periods to be a function of the demand history. Even with linear costs, the general model [GM] is likely to be large and not amenable for easy solution with standard software packages. Hence we developed an algorithm based on augmented Lagrangian method and restricted simplicial decomposition. Our computational results suggest that this algorithm is effective in solving problems with up to 5000 scenarios. These results indicate that optimal strategy often involves a mix of technologies that depend on risk factors, demand levels and cost parameters and hence require a systematic approach such as the one developed in this paper. Finally, we demonstrated the versatility of our approach by deriving a special case of [GM] for tactical decisions related to new product introduction while following a flexible technology strategy, and illustrated its application using data from the case of Eli Lilly and Company. It may be noted that the general model permits a number of extensions in a fairly routine manner. For the sake of brevity, we do not discuss the details, and only mention a few. While we have only considered the two extreme technologies (dedicated and completely flexible), it is easy to add other technologies that provide some types of partial flexibility. These include technologies that are capable of producing a predefined subset of products. Second, for ease of exposition we did not consider retirement of capacity with age. This feature could be added easily without complicating the model and the solution approach. Other desirable extensions may be more involved and require further work. For example, inclusion of uncertainty in technological developments and / or costs significantly increases the problem complexity and may require a different approach. Second we have considered only product mix flexibility in our model. Consideration of other benefits of flexible technology, such as improved quality, faster response time raise a number of modeling issues that are not easy to incorporate within the stochastic program developed in this paper. Finally, it might be of interest to identify and model the impact of other benefits of modern technologies. For example, reported evidence suggests that improvements in quality and response time are likely to have a positive influence on customers and thus demand itself may be a function of technology choice.

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References

[1] Bai, D., T. Carpenter and J.M. Mulvey. 1994. "Stochastic Programming to Promote Network Survivability". Technical Report SOR-94-14, Department of Civil Engineering and Operations Research, Princeton University.

[2] Bertsekas, D.P. 1982. *Constrained Optimization and Lagrangian Multiplier Methods*, Academic Press.

[3] Birge, J.R. and F. Louveaux. 1997. *Introduction to Stochastic Programming*, Springer.

[4] Chakravarty, A.K. 1989. "Analysis of Flexibility with Rationing for a Mix of Manufacturing Facilities". *The International Journal of Flexible Manufacturing Systems* 2:1, 43-62.

[5] Chen, Z.-L., S. Li and D. Tirupati. 1998. "Capacity and Technology Choices with Dynamic Uncertain Demands-A Scenario-Based Stochastic Programming Approach". *Proceeding of International Conference of Management*, Shanghai, China, July 25-29.

[6] Cohen, M.A. and R.M. Halperin. 1986. "Optimal Technology Choice in a Dynamic-Stochastic Environment". *Journal of Operations Management* 6:3, 317-331.

[7] CPLEX Optimization, Inc. 1995. "Using the CPLEX Callable Library". Incline Village, NV.

[8] Dantzig, G.B. and P. Wolfe. 1960. "Decomposition Principle for Linear Programs". *Operations Research* 8, 101-111.

[9] Eppen, G.D., R.K. Maritin, and L. Schrage. 1989. "A Scenario Approach to Capacity Planning". *Operations Research* 37:4, 517-527.

[10] Fine, C.H. 1993. "Developments in Manufacturing Technology and Economic Evaluation". In *Logistics in Production and Inventory, Handbook in Operations Research and Management Science*, Vol 4, Edited by Graves, S. C., A. H. G. Rinnooy kan and P. Zipkin (eds.) Elsevier Science, North Holland.

[11] Fine, C.H. and R.M. Freund. 1990. "Optimal Investment in Product-Flexible Manufacturing Capacity". *Management Science* 36, 449-466.

[12] Finnie, J. 1988. "The Role of Financial Appraisal in Decisions to Acquire Advanced Manufacturing Technology". *Accounting and Business Research* 18, 133-139.

[13] Gerwin, D. 1989. "Manufacturing Flexibility in CAM Era". *Business Horizon* 37, 410-425.

[14] Hearn, D.W., S. Lawphongpanich and J.A. Ventura. 1985. "Finiteness in Restricted Simplicial Decomposition". *Operations Research Letters* 3, 125-130.

[15] Kaplan, R.S. 1986. "Must CIM Be Justified by Faith Alone?". *Harvard Business Review* 64:2, 87-95.

[16] Li, S. and J. Qiu. 1996. "Models for Capacity Acquisition Decisions Considering Operational Costs". *The International Journal of Flexible Manufacturing Systems* 8:3, 211-230.

[17] Li, S and D. Tirupati. 1992. "Technology Selection and Capacity Planning for Manufacturing System". In *Intelligent Design and Manufacturing*, A. Kusiak (ed.) John Wiley and Sons, New York.

[18] Li, S. and D. Tirupati. 1994. "Dynamic Capacity Expansion Problem with Multiple Products: Technology Selection and Timing of Capacity Additions". *Operations Research* 42, 958-976.

[19] Li, S. and D. Tirupati. 1995. "Technology Choice with Stochastic Demands and Dynamic Capacity Allocation: A Two-product Analysis". *Journal of Operations Management* 22:3, 239-258.

[20] Li, S. and D. Tirupati. 1996. "Impact of Product Mix Flexibility and Allocation Policies on Technology Choice". *Computer and Operations Research.* (Forthcoming)

[21] Mahajan, V., E. Muller and F.M. Bass. 1990. "New Product Diffusion Models in Marketing: A Review and Directions for Research". *Journal of Marketing* 54, 1-26.

[22] Mahajan, V. and Y. Wind 1986. "Innovation Diffusion Models of New Product Acceptance". *Econometrics and Management Science*, Vol. 5, Ballinger publishing, Mass.

[23] Mulvey, J.M. and A. Ruszczynski. 1992."A Diagonal Quadratic Approximation Method for Large-scale Linear Programs". *Operations Research Letters* 12, 205-215.

[24] Pisano, G. and S. Rossi. 1994. " Eli Lilly and Company: The Flexible Facility Decision". *Harvard Business School Case Series*, 9-694-074, April 21.

[25] Pierskella, W. P. and J. A. Voelker. 1976. " A Survey of Maintenance Models: The Control and Surveillance of Deteriorating Systems". *Naval Research Logistics Quarterly*, 353-388.

[26] Sethi, A.K. and S.P. Sethi. 1990. " Flexibility in Manufacturing: A Survey". *The International Journal of Flexible Manufacturing Systems* 2, 289-328.

[27] Swamidass, P. M. and M. A. Waller. 1990. " A Classification of Approaches to Planning and Justifying New Manufacturing Technologies". *Journal of Manufacturing Systems* 9:1, 181-193.

[28] Von Hohenbalken, B.V. 1977." Simplicial Decomposition in Nonlinear Programming Algorithms". *Mathematical Programming* 13, 49-68.

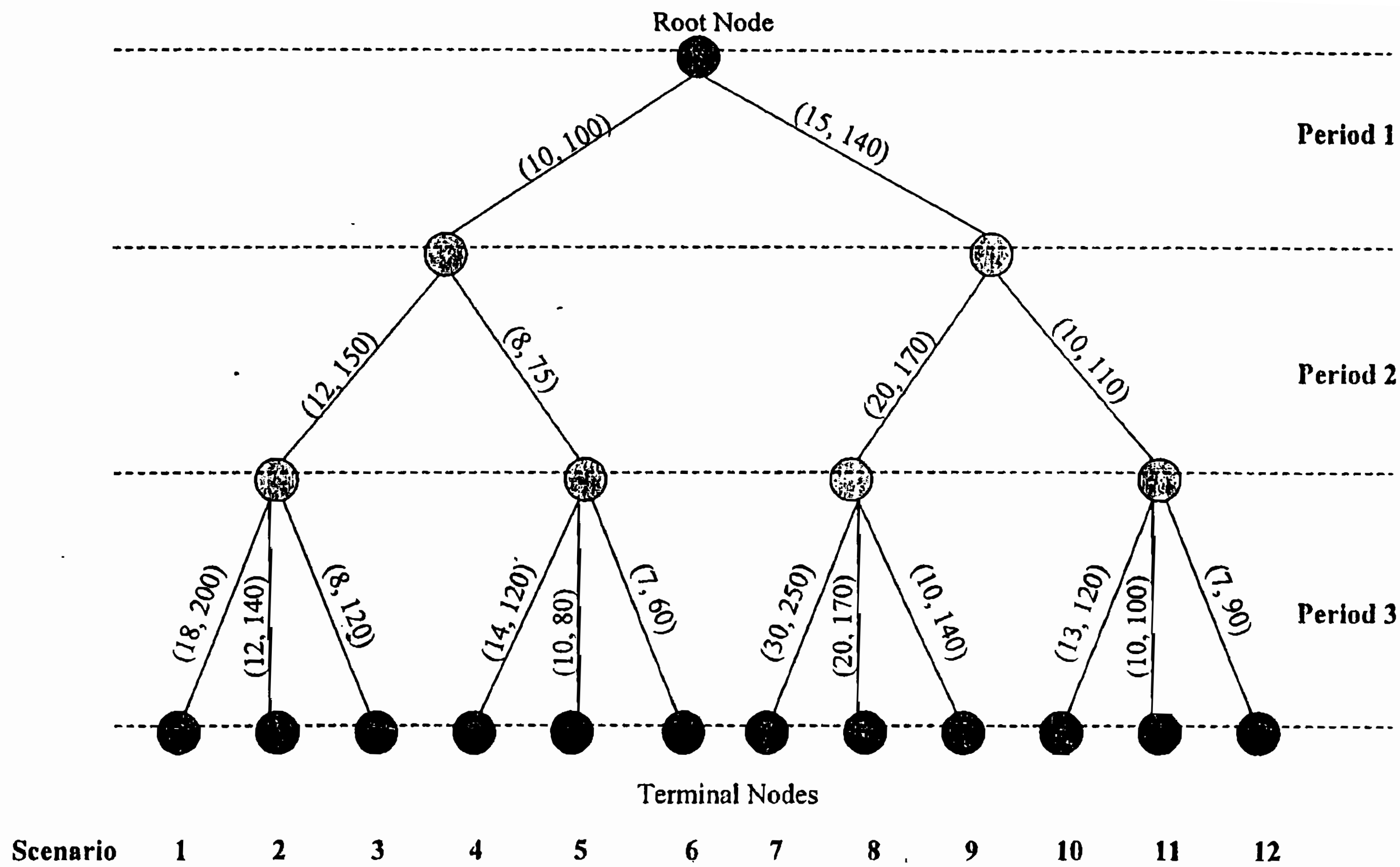

Figure 1: A tree structure of scenarios for demand realizations of two products over three periods

Table 1: Design of Test Problems with Model [GM]

Number of products: 2
Planning horizon length: 8 periods for robustness experiment; 5 periods for impact experiment
Total demand variability (2 levels): $R = 0.2$, and 0.4
Individual demand variability (2 levels): $W = 0.2$, and 0.4

Time Period			1	2	3	4	5	6	7	8
4 Cases of Unit Investment Costs	Case 1	Flexible Capacity	250	225	203	182	164	148	133	120
		Dedicated Capacity	200	180	162	146	131	118	106	95
	Case 2	Flexible Capacity	300	270	243	219	197	177	160	144
		Dedicated Capacity	200	180	162	146	131	118	106	95
	Case 3	Flexible Capacity	350	315	284	255	230	207	186	168
		Dedicated Capacity	200	180	162	146	131	118	106	95
	Case 4	Flexible Capacity	400	360	324	292	262	236	212	191
		Dedicated Capacity	200	180	162	146	131	118	106	95
3 Cases of Unit Operating Costs	Case 1	Flexible Capacity	130	117	105	95	85	77	69	62
		Dedicated Capacity	100	90	81	73	66	59	53	48
	Case 2	Flexible Capacity	100	90	81	73	66	59	53	48
		Dedicated Capacity	100	90	81	73	66	59	53	48
	Case 3	Flexible Capacity	70	63	57	51	46	41	37	34
		Dedicated Capacity	100	90	81	73	66	59	53	48
3 Scenario Structures for Robustness Experiment	Case 1	Number of Joint Demand Outcomes	9	6	2	2	2	2	2	2
	Case 2		6	6	4	2	2	2	2	2
	Case 3		4	4	4	4	2	2	2	2
3 Scenario Structures for Impact Experiment	Case 1	Number of Joint Demand Outcomes	16	9	4	2	2			
	Case 2		9	9	4	4	2			
	Case 3		6	6	6	4	4			

Table 2: Test Results of Robustness Experiment

Investment Costs		Case 1			Case 2			Case 3			Case 4		
Operating Costs		Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case1	Case 2	Case 3
E_6	Avg	0.083%	0%	0%	0.047%	0.001%	0.083%	0.029%	0.012%	0.092%	0%	0.004%	0%
	Max	0.163%	0%	0%	0.101%	0.005%	0.120%	0.056%	0.033%	0.184%	0%	0.038%	0.002%
E_7	Avg	0.196%	0%	0%	0.127%	0.001%	0.221%	0.097%	0.006%	0.328%	0%	0.000%	0.019%
	Max	0.424%	0%	0%	0.238%	0.007%	0.348%	0.188%	0.028%	0.774%	0%	0.005%	0.049%
E_8	Avg	0.291%	0%	0%	0.226%	0.001%	0.346%	0.170%	0.003%	0.453%	0%	0%	0.048%
	Max	0.621%	0%	0%	0.730%	0.010%	0.600%	0.302%	0.016%	0.920%	0%	0.004%	0.169%

Table 3: Test Results of Impact Experiment with R=0.2, W=0.2

Total Demand Variability $R = 0.2$ Individual Demand Variability $W = 0.2$													
Unit Investment Costs		Case 1			Case 2			Case 3			Case 4		
Unit Operating Costs		Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case1	Case 2	Case 3
Flexible Cap. in t / Total Flexible Cap.	t=1	0.6284	0.8471	0.8148	0.5476.	0.8588	0.9593	0.4618	0.8397	0.9403	0.0000	0.3253	0.9044
	t=2	0.1141	0.0734	0.0747	0.1315	0.0608	0.0407	0.1167	0.0485	0.0199	0.0000	0.2715	0.0363
	t=3	0.0486	0.0159	0.0412	0.0536	0.0134	0.0000	0.0416	0.0137	0.0061	0.0000	0.1130	0.0091
	t=4	0.0841	0.0274	0.0694	0.0991	0.0212	0.0000	0.0979	0.0257	0.0092	0.0000	0.1194	0.0129
	t=5	0.1249	0.0362	0.0000	0.1683	0.0459	0.0000	0.2793	0.0725	0.0246	0.0000	0.1707	0.0373
Total Flex. Cap. in t / Total Cap. in t	t=1	0.1471	0.3653	1.0000	0.0876	0.3521	0.9610	0.0316	0.2937	0.4300	0.0000	0.0597	0.3878
	t=2	0.1656	0.3642	1.0000	0.1053	0.3448	0.9136	0.0391	0.2833	0.3986	0.0000	0.0605	0.3666
	t=3	0.1737	0.3536	1.0000	0.1131	0.3349	0.8718	0.0415	0.2765	0.3825	0.0000	0.0656	0.3535
	t=4	0.1908	0.3383	0.9982	0.1294	0.3188	0.8111	0.0511	0.2674	0.3584	0.0000	0.0732	0.3322
	t=5	0.2047	0.3094	0.8746	0.1546	0.2965	0.7128	0.0833	0.2618	0.3234	0.0000	0.0836	0.3048
Flexible Investment Cost / Total Investment Cost		0.2309	0.3722	0.9245	0.1965	0.3995	0.8230	0.1161	0.3711	0.4750	0.0000	0.1360	0.4834
Flexible Operating Cost / Total Operating Cost		0.1580	0.3500	0.9616	0.0939	0.3342	0.8210	0.0339	0.2844	0.3086	0.0000	0.0743	0.2824
All Flexible Cost / Optimal Cost		1.1935	1.0600	1.0040	1.2414	1.1175	1.0201	1.3271	1.1741	1.0624	1.4062	1.2337	1.1195
All Dedicated Cost / Optimal Cost		1.0297	1.0744	1.2332	1.0134	1.0454	1.1379	1.0025	1.0198	1.0854	1.0000	1.0000	1.0549

Table 4: Test Results of Impact Experiment with R=0.2, W=0.4

Total Demand Variability $R = 0.2$ Individual Demand Variability $W = 0.4$													
Unit Investment Costs		Case 1			Case 2			Case 3			Case 4		
Unit Operating Costs		Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case1	Case 2	Case 3
Flexible Cap. in t / Total Flexible Cap.	t=1	0.7215	0.8553	0.8146	0.6644	0.8565	0.9248	0.5665	0.8621	0.9257	0.0000	0.8084	0.9043
	t=2	0.1351	0.0638	0.0747	0.1330	0.0682	0.0565	0.1534	0.0565	0.0279	0.0000	0.0832	0.0385
	t=3	0.0407	0.0194	0.0411	0.0434	0.0156	0.0071	0.0463	0.0139	0.0104	0.0000	0.0258	0.0109
	t=4	0.0613	0.0343	0.0694	0.0693	0.0263	0.0035	0.0816	0.0242	0.0137	0.0000	0.1185	0.0160
	t=5	0.0654	0.0272	0.0003	0.0899	0.0336	0.0081	0.1521	0.0434	0.0223	0.0000	0.0516	0.0303
Total Flex. Cap. in t / Total Cap. in t	t=1	0.3059	0.7480	1.0000	0.1731	0.7172	0.9666	0.0578	0.6433	0.8404	0.0000	0.2122	0.7813
	t=2	0.3374	0.7353	1.0000	0.2011	0.7062	0.9448	0.0716	0.6211	0.7874	0.0000	0.2107	0.7401
	t=3	0.3470	0.7167	1.0000	0.2092	0.6868	0.9080	0.0653	0.6054	0.7620	0.0000	0.2104	0.7143
	t=4	0.3591	0.6899	0.9983	0.2221	0.6558	0.8468	0.0861	0.5816	0.7138	0.0000	0.1934	0.6717
	t=5	0.3596	0.6245	0.8749	0.2330	0.5990	0.7495	0.1051	0.5451	0.6417	0.0000	0.2046	0.6099
Flexible Investment Cost / Total Investment Cost		0.4050	0.6993	0.9247	0.3006	0.7121	0.8508	0.1560	0.6913	0.7838	0.0000	0.3240	0.7790
Flexible Operating Cost / Total Operating Cost		0.3432	0.7155	0.9616	0.1837	0.6900	0.8561	0.0552	0.6306	0.7009	0.0000	0.2512	0.6509
All Flexible Cost / Optimal Cost		1.1029	1.0295	1.0040	1.1587	1.0577	1.0189	1.2046	1.0856	1.0423	1.2749	1.1186	1.0692
All Dedicated Cost / Optimal Cost		1.0495	1.1510	1.3602	1.0205	1.0913	1.2536	1.0036	1.0401	1.1744	1.0000	1.0000	1.1112

Table 5: Test Results of Impact Experiment with R=0.4, W=0.2

Total Demand Variability $R = 0.4$ Individual Demand Variability $W = 0.2$													
Unit Investment Costs		Case 1			Case 2			Case 3			Case 4		
Unit Operating Costs		Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case1	Case 2	Case 3
Flexible Cap. in t / Total Flexible Cap.	t=1	0.6833	0.8077	0.7930	0.6375	0.8171	0.9412	0.5509	0.8260	0.8878	0.0000	0.3463	0.8482
	t=2	0.1027	0.0887	0.0912	0.1025	0.0848	0.0423	0.1270	0.0691	0.0439	0.0000	0.2562	0.0623
	t=3	0.0667	0.0287	0.0555	0.0570	0.0266	0.0016	0.0487	0.0252	0.0170	0.0000	0.1496	0.0244
	t=4	0.0656	0.0361	0.0603	0.0769	0.0296	0.0053	0.0707	0.0269	0.0209	0.0000	0.1158	0.0246
	t=5	0.0931	0.0389	0.0000	0.1261	0.0419	0.0097	0.2028	0.0529	0.0328	0.0000	0.1320	0.0406
Total Flex. Cap. in t / Total Cap. in t	t=1	0.1889	0.3649	1.0000	0.1272	0.3649	0.7512	0.0670	0.3395	0.4300	0.0000	0.0838	0.3825
	t=2	0.2005	0.3137	1.0000	0.1366	0.3611	0.6903	0.0584	0.3282	0.3912	0.0000	0.0792	0.3647
	t=3	0.2074	0.3521	0.9984	0.1436	0.3488	0.6463	0.0612	0.3174	0.3791	0.0000	0.0846	0.3512
	t=4	0.2149	0.3391	0.9828	0.1553	0.3334	0.6017	0.0676	0.3039	0.3584	0.0000	0.0912	0.3334
	t=5	0.2240	0.3184	0.8832	0.1750	0.3145	0.5472	0.0982	0.2924	0.3337	0.0000	0.0993	0.3144
Flexible Investment Cost / Total Investment Cost		0.2585	0.3779	0.9255	0.2286	0.4171	0.6647	0.1421	0.4270	0.4805	0.0000	0.1535	0.4834
Flexible Operating Cost / Total Operating Cost		0.1695	0.3580	0.9577	0.1067	0.3549	0.6316	0.0410	0.3279	0.3382	0.0000	0.0819	0.3170
All Flexible Cost / Optimal Cost		1.1906	1.0629	1.0042	1.2555	1.1225	1.0524	1.3247	1.1814	1.0779	1.4057	1.2224	1.1436
All Dedicated Cost / Optimal Cost		1.0366	1.0819	1.2303	1.0172	1.0509	1.1200	1.0035	1.0224	1.0915	1.0000	1.0100	1.0530

Table 6: Test Results of Impact Experiment with R=0.4, W=0.4

Total Demand Variability $R = 0.4$ Individual Demand Variability $W = 0.4$													
Unit Investment Costs		Case 1			Case 2			Case 3			Case 4		
Unit Operating Costs		Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case1	Case 2	Case 3
Flexible Cap. in t / Total Flexible Cap.	t=1	0.7150	0.8112	0.7911	0.6800	0.8185	0.8607	0.6158	0.8239	0.8541	0.0000	0.6058	0.8405
	t=2	0.1104	0.0807	0.0910	0.1130	0.0821	0.0711	0.1311	0.0780	0.0594	0.0000	0.1672	0.0688
	t=3	0.0526	0.0342	0.0553	0.0587	0.0291	0.0281	0.0539	0.0275	0.0279	0.0000	0.0907	0.0278
	t=4	0.0596	0.0416	0.0606	0.0666	0.0336	0.0211	0.0707	0.0291	0.0283	0.0000	0.0578	0.0277
	t=5	0.0624	0.0323	0.0019	0.0817	0.0367	0.0191	0.1286	0.0417	0.0304	0.0000	0.0785	0.0352
Total Flex. Cap. in t / Total Cap. in t	t=1	0.3436	0.7398	1.0000	0.2137	0.7323	0.8806	0.0852	0.6964	0.7953	0.0000	0.1779	0.7567
	t=2	0.3710	0.7278	1.0000	0.2337	0.7204	0.8497	0.0966	0.6790	0.7540	0.0000	0.1852	0.7288
	t=3	0.3829	0.7090	0.9984	0.2463	0.6970	0.8193	0.1018	0.6576	0.7280	0.0000	0.1877	0.7038
	t=4	0.3891	0.6861	0.9834	0.2595	0.6680	0.7742	0.1115	0.6284	0.6930	0.0000	0.1899	0.6689
	t=5	0.3929	0.6478	0.8850	0.2710	0.6255	0.7112	0.1320	0.5949	0.6443	0.0000	0.1923	0.6256
Flexible Investment Cost / Total Investment Cost		0.4411	0.7054	0.9268	0.3464	0.7291	0.8073	0.1951	0.7311	0.7757	0.0000	0.2855	0.7820
Flexible Operating Cost / Total Operating Cost		0.3534	0.7208	0.9584	0.2010	0.7099	0.7973	0.0679	0.6806	0.7128	0.0000	0.2238	0.6856
All Flexible Cost / Optimal Cost		1.1005	1.0311	1.0042	1.1446	1.0601	1.0229	1.1982	1.0874	1.0513	1.2692	1.1192	1.0794
All Dedicated Cost / Optimal Cost		1.0611	1.1624	1.3626	1.0271	1.0993	1.2561	1.0053	1.0439	1.1790	1.0000	1.0000	1.1138

Table 7: Design of Test Problems with Model [NPI]

Number of products: 3 (A, B, C) Number of phases: 3 Number of time periods: 5 Purchase cost of flexible capacity: 0 Purchase cost of dedicated capacity: $6250 / unit Operating cost of flexible capacity: $1352 / kg					
Phase	1	2	3		
Success Probability	0.1 0.3 0.5 0.7 0.9	0.4 0.5 0.6			
Number of Demand Outcomes Probability of Outcomes	1	1	3 0.3 0.4 0.3 0.4 0.4 0.2 0.2 0.4 0.4		
Time Period	1	2	3	4	5
Yield from ded. Capacity (kg/unit)	20,000	16,000	20,000	20,000	20,000
Op. cost of flex. Capacity ($/kg)	1.352	1.352	1.352	1.352	1.352
Op. cost of ded. Capacity ($/unit)	5,660	4,528	5,660	5,660	5,660
Demand Outcomes					
Product A					
High	1,000	5,000	100,000	160,000	80,000
Medium			50,000	80,000	40,000
Low			25,000	40,000	20,000
Product B					
High	1,000	2,000	30,000	40,000	20,000
Medium			15,000	20,000	10,000
Low			7,500	10,000	5,000
Product C					
High	1,000	1,000	7,000	10,000	5,000
Medium			3,500	5,000	2,500
Low			1,750	2,500	1,250

Table 8: Test Results with [NPI] – Optimal vs. Extreme Strategies

Success Probability In Phase I	A		B		C	
	All ded. / Optimal	All flex / Optimal	All ded. / Optimal	All flex / Optimal	All ded. / Optimal	All flex / Optimal
0.1	2.224	2.627	4.155	2.092	7.776	1.039
0.3	1.415	2.627	2.334	2.092	3.678	1.039
0.5	1.252	2.627	1.872	2.092	2.856	1.039
0.7	1.182	2.627	1.674	2.092	2.504	1.039
0.9	1.143	2.627	1.564	2.092	2.308	1.039

Table 9: Test Results with [NPI] – Role of Flexible Technology

Performance Measure	A	B	C
Periods in which flexible capacity is used	1, 2	1, 2, 3	1, 2, 3, 4, 5
Usage of flexible capacity	100% (t = 1, 2)	100% (t = 1, 2) 33% (t = 3)	100% (t = 1, 2, 3) 27% (t = 4) 16% (t = 5)
Flexible Operating Cost / Total Operating Cost	0.1392	0.3449	0.7377

Note (i) Usage of flexible capacity = $\frac{\text{Flexible Capacity Used in } t}{\text{Total Available Capacity in } t}$

Total available capacity in t = flexible capacity used in period t + dedicated capacity available in period

(ii) The results in this table are independent of success probability in phase 1 and phase 2.