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BENCHMARKING OF A STOCHASTIC PRODUCTION PLANNING MODEL IN A SIMULATION TESTBED

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ABSTRACT

A major problem in production planning is to determine when to release products into production to meet forecasted requirements. Recently, Riaño et al. (2002) proposed the *Stochastic Production Planning* (SPP) model for a multi-period, multi-product system, where the lead time to produce a product may be random. The model determines release times for the products that ensure the requirements in each time period are met with desired probabilities at a minimum cost. This paper describes how an advanced planning model like SPP can be integrated with discrete event simulation models to make the simulations more realistic and informative. This paper also compares the performance of the SPP model with the classical MRP (materials requirements planning) model, and with a stochastic variation of the MRP model in a simulation study. The costs associated with the production plans from SPP are about 10% less than the costs from the other two models.

1 INTRODUCTION

Production plans have major affects on costs and customer service levels. In addition, companies use production plans for many activities related to actual production, such as negotiating when to purchase parts and supplies from vendors, setting inventory levels in various stages of production, scheduling personnel, and informing customers of realistic delivery dates. It is especially crucial for the operational planning of supply chains.

Today's state-of-the-art advanced planning and scheduling (APS) systems take information about customer demand, and historical information about supply chain performance, and generate material planning and control decisions that are intended to be feasible. Because of the deterministic nature of this process, there are limitations to these planning approaches when it comes to actual execution of such plans.

Lendermann et al. (2002) described the importance of incorporating APS procedures with discrete event simulation (DES). This enables more realistic planning of manufacturing facilities and supply chains. Moreover, as stochastic APS procedures are formulated to account for the stochastic nature of production processes, DES can be used to test the operations of these APS.

There are a variety of MRP software packages on the market that determine production plans; see for instance (Elliot 2000). The main factor in determining release times is the *lead time* to produce a product, which is the total time from when the product is released into the system to the time it is finished. MRP is based on the assumption that the lead time of a product is a nonrandom constant. Typically the expected lead time inflated by some factor is used.

There are other types of advanced production planning models that do not consider uncertainties. One approach is to use linear or nonlinear programming models to select release times that minimize costs subject to capacity or resource constraints, assuming "ideal" nonrandom production flows over time; see for instance (Hackman and Leachman 1989, Leachman et al. 1996). There are also ad hoc production planning models based on variations of the classical Newsvendor and Economic Order Quantity models. These models, like MRP, are not designed to handle uncertainties associated with random lead times that are dependent on

the load in the system, changing requirements, machine breakdowns, rework or scrapping of products, delays in supplies, personnel availability, etc. (Baker 1993, Gumaer 1996). Because of the complicated nature of stochastic production systems, optimal production plans cannot be obtained by standard applications of stochastic queueing networks, inventory systems, or dynamic programming.

This paper describes a *Stochastic Production Planning* (SPP) model for a system with random lead times and requirements recently proposed in Riaño et al. (2002). The model addresses production planning at a high-level in a company or a supply chain, which is different than lower-level machine scheduling that determines what job to process next from a specified set of jobs. The SPP model is a linear program (LP) that determines quantities of products to release into production in each time period that provide the desired quality of service at minimum cost. Multiple types of products are released into the system over a finite time horizon to ensure that the requirements in each time period are met with desired probabilities at minimum costs. The model also allows for backorders. The model is implemented via a rolling-horizon procedure. Here we describe the main ideas of the model. For fuller treatment, see Riaño et al. (2002). In this paper, we also illustrate how an advanced planning procedure like the SPP model can be integrated into discrete event simulation models to facilitate better understanding and planning of manufacturing and supply chain networks.

The remainder of this paper is organized as follows. Section 2 reviews the production system we are considering and describes the development of the SPP model. Section 3 describes the rolling-horizon implementation of the SPP model and how it can be adapted and integrated with a DES model. Section 4 describes two other production planning models, the classical MRP model and a more intelligent stochastic myopic control model called the *Mypoic Requirements Planning* (MyRP) model, that we use for comparison. Section 5 illustrates how the three planning models can be integrated into a discrete event simulation model of a manufacturing network, and compares the performance of the three models in a simulation study. The results show that costs associated with the production plans from our model tend to be about 10% less than costs from these two alternative models in most cases.

2 STOCHASTIC PRODUCTION PLANNING MODEL

We consider a production system or supply chain network that produces I types of products for its customers over a discrete-time planning horizon of length T. The issue is to determine the quantity x_{it} of product i to release into production in time period t, for each $i = 1, \ldots, I$ and $t = 1, \ldots, T$. The SPP model allows products to be released at some rate during each period, but here we assume that the products are released into production at the "beginning" of the time periods and the requirements are satisfied at the "end" of the periods. The rest of this section describes how the system operates and the formulation of the model.

2.1 Requirements

The production requirements for the system are represented by the *cumulative requirement* R_{it} of product i required in periods $1, \ldots, t$ (up to the "end" of period t). These requirements may be deterministic values, or random variables with specified distributions, based on sales forecasts, management decisions, or other information.

2.2 Lead Times and Expected Outputs

The lead times to produce parts in a manufacturing facility or network depend on the network structure, protocols, machine scheduling rules, etc. We assume that the *lead time* for type i products are independent random variables with a specified *probability distribution* $F_i(t)$. These distributions may be estimated from production data or other system information. Such a single-stage lead time may actually represent the time for several production stages or tasks in a multi-station production network. The lead-times determine the output process. In particular, the expected output in time period t from the x_{is} products started in time period s is $x_{is}F_i(t-s+1)$.

The initial work-in-progress (WIP) in the system also contributes to the output process. We let $w_{i0}(k)$ denote the *initial WIP* at the beginning of the time horizon that has been in the system for k periods, and let M denote the *maximum age* of the WIP at time 0. Then of the $w_{i0}(k)$ products that have been in the system for k time units, the expected number of these that are output in time period t is $w_{i0}(k)F_i(t;k)$, where $F_i(t;k)$ is the conditional lead-time distribution, conditioned that the lead time is greater than k.

It follows that the *expected cumulative output* for product i in periods $1, \ldots, t$ (up to the "end" of period t) is given by

$$Y_{it} = \sum_{k=1}^{\mathrm{M}} w_{i0}(k)F_i(t;k) + \sum_{s=1}^{t} x_{is}F_i(t-s+1), \qquad (1)$$

where the first sum is the expected output from the WIP at time 0, and the second sum is the expected output from the quantities released up to period t.

2.3 Costs

We consider three costs associated with each product i in period t:

- A *late cost* c_{it} for each unit of product i that is backlogged in period t.
- An *early cost* h_{it} for holding a finished unit in inventory.
- An *in-transit cost* $\bar{h}_{it}$ for a unit that is being processed.

In selecting release quantities, one aim is to minimize the sum of these system costs. The objective function we will use in this regard is

$$\sum_{i=1}^{I}\sum_{t=1}^{T}\Big[c_{it}(R_{it}-Y_{it})^{+}+h_{it}(R_{it}-Y_{it})^{-} +\bar{h}_{it}[\sum_{k=1}^{M}w_{i0}(k)+\sum_{s=1}^{t}x_{is}-Y_{it-1}]\Big]. \quad (2)$$

Here $a^{+}=\max\{0,a\}$, $a^{-}=-\min\{0,a\}$.

The first line is an approximation for the expected late plus early cost, which is $c_{it}E(R_{it}-\tilde{Y}_{it})^{+}+h_{it}E(R_{it}-\tilde{Y}_{it})^{-}$, where $\tilde{Y}_{it}$ is the random cumulative output of product i up to period t. The first line is a linear function of the input quantities (since Y_{it} given by (1) is), but the expected late plus early cost is a nonlinear function of the inputs. The term on the last line is the expected WIP of product i being processed in period t: the input up to time t minus the cumulated expected output.

2.4 Quality of Service

To determine optimal quantities x_{it} to release into the system, trade-offs between early and late costs are one consideration. In addition, manufacturers often want to guarantee a certain quality of service for its customers to the effect that deliveries to them will be on time with a high probability. This QOS is often given a higher priority than reducing holding costs, since long-run customer satisfaction usually affects profits more than holding costs do.

For our system, the QOS criterion is to ensure that the cumulative quantity of product i delivered by each period t meets the requirements R_{it} with a specified *QOS probability* α_{it}. In other words, the *QOS criterion* is

$$P\{\tilde{Y}_{it}\geq R_{it}\}\geq\alpha_{it}, \qquad \text{for each } i \text{ and } t, \quad (3)$$

where $\tilde{Y}_{it}$ denotes the random quantity of product i delivered by period t. Recall that $\tilde{Y}_{it}$ has a mean Y_{it} given by (1).

To convert this stochastic constraint into a linear constraint involving only expectations, the cumulative output $\tilde{Y}_{it}$ is modeled as a Poisson random variable.

Remark 1 **QOS Criterion** *The QOS criterion (3) is equivalent to*

$$Y_{it}\geq\mu_{it}, \qquad \textit{for each } i \textit{ and } t \quad (4)$$

where

$$\mu_{it}=\min\left\{\mu:\sum_{n=0}^{\infty}\left(P\{R_{it}=n\}\cdot e^{-\mu}\sum_{k=n}^{\infty}\mu^{k}/k!\right)\geq\alpha_{it}\right\}. \quad (5)$$

See Riaño et al. (2002) for justification and derivation.

The equivalent QOS criterion (4) is a linear inequality of the release quantities x_{it}'s, since the expected output Y_{it} given by (1) is a linear function of the x_{it}'s. The μ_{it}'s, which are functions of the specified requirement probabilities $P\{R_{it}=n\}$, can be computed directly from (5) and used as input data for optimizing the x_{it}'s by the LP in the next subsection.

2.5 Auxiliary Constraints

The last feature of the production system are *auxiliary constraints* related to resources, personnel scheduling, etc., that affect the production flows. The SPP model can contain constraints that are linear functions of the release quantities x_{it}. For illustrative purposes, we will include the constraints

$$a_t\leq\sum_{i=1}^{I}(x_{it}-x_{i(t-1)})\leq b_t, \qquad t=2,\ldots,T. \quad (6)$$

This ensures a smoother production loading by bounding the difference between release quantities in adjacent periods. Additional upper and lower bound constraints on release quantities that one might use are

$$\hat{a}_{it}\leq x_{it}\leq\hat{b}_{it}, \qquad \text{or} \qquad \tilde{a}_{it}\leq\sum_{s=1}^{t}x_{is}\leq\tilde{b}_{it}.$$

Additional linear capacity constraints can also be incorporated to reflect manufacturing capacity, resource capacity or WIP constraints.

2.6 LP Optimization

This subsection describes SPP as a linear program (LP) for optimizing the release quantities for the production system described in the preceding section. A dynamic implementation of this linear program is discussed in the next section.

For the system described above, the general aim is to find optimal release quantities x_{it}'s that minimize the system cost function (2) subject to the quality of service constraints

(4), and the production smoothing constraint (6). Although we consider here only the quality of service and production smoothing constraints, additional linear constraints on the manufacturing capacity or WIP can be easily incorporated.

Our approach to the problem is to use a dynamic implementation of a linear program. The linear program we will use is as follows.

$$\min_{x_{it},u_{it},z_{it}} \sum_{i=1}^{I}\sum_{t=1}^{T}\Big[c_{it}u_{it} + h_{it}z_{it} + \bar{h}_{it}\left(\sum_{k=1}^{M} w_{i0}(k) + \sum_{s=1}^{t} x_{is} - Y_{it}\right)\Big], \quad (7)$$

such that

$$\begin{aligned} Y_{it} &= \sum_{k=1}^{M} w_{i0}(k)F_i(t;k) + \sum_{s=1}^{t} x_{is}F_i(t-s+1) \\ Y_{it} &\geq \mu_{it} \qquad (8) \\ a_t &\leq \sum_{i=1}^{I}(x_{it} - x_{i(t-1)}) \leq b_t \\ u_{it} &\geq R_{it} - Y_{it} \\ z_{it} &\geq Y_{it} - R_{it}, \qquad i = 1,\ldots,I, \quad t = 1,\ldots,T, \\ x_{it},\ u_{it},\ z_{it} &\text{ are nonnegative.} \end{aligned}$$

The u_{it}'s and z_{it}'s are artificial variables introduced to make the objective function linear. When the cost is minimized, they are forced to be

$$u_{it} = (R_{it} - Y_{it})^+, \qquad z_{it} = (R_{it} - Y_{it})^- .$$

Note that either u_{it} or z_{it} is 0, and $u_{it} + z_{it} = |R_{it} - Y_{it}|$.

The LP above provides a " static" optimization of the release quantities for a fixed planning horizon. To use the model in a simulation or for actual planning over a series of time periods, one would run the LP in each time period with updated information as described in the next section.

3 IMPLEMENTATION OF THE MODEL

To represent demand driven production environments, incorporating APS procedures in DES is a practical way of translating customer demand into feasible input rates (Lendermann et al. 2002). This section describes how the SPP model formulated as an LP in the previous section would be used to generate production plans for a series of time periods in a simulation.

The model would naturally be implemented by a *rolling-horizon procedure* as follows. At the beginning of each time period, the system would perform the following steps:

- Observe the production output from the previous period and the current WIP quantities $w_{i0}(k)$.
- Update the requirements for the next T time periods based on new demand forecasts and the previous period output (increase or decrease future requirements by backlogged products or extra finished products, respectively, from previous period).
- Run the LP with the current WIP and updated requirements for the new time horizon to obtain optimal release quantities x_{it}.
- Release the quantities x_{i1} into the system for the current production period (the optimal quantities x_{it} for periods $t \geq 2$ are "forecasts" of future release quantities).

This procedure would yield production release times generated one period at a time, at the beginning of each simulated period.

Incorporating SPP in a DES model facilitates more realistic representations of supply chain models and dynamics, and enables better evaluations of alternative production or supply chain strategies. Figure 1 illustrates how this rolling horizon SPP procedure can be incorporated with a conventional simulation model to extend the traditional scope of simulation studies.

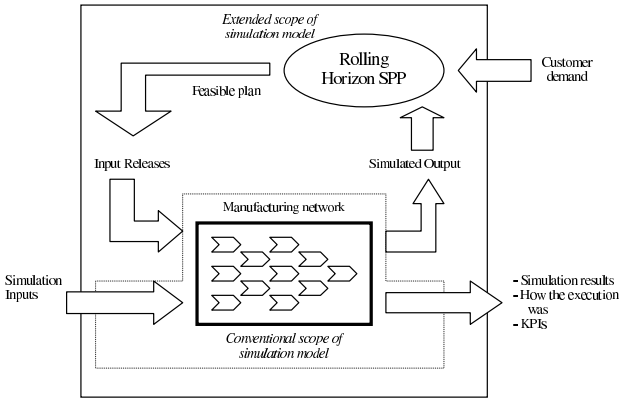

Figure 1: Extended Scope of Simulation Study: Incorporating SPP with Conventional Models

As SPP explicitly accounts for the stochastic nature of demand and lead times, DES is a practical approach to test its performance. In Section 5, SPP is integrated with a DES model like above to test its performance against two other planning procedures.

4 COMPARISON WITH MRP-TYPE CONTROL POLICIES

To assess the quality of the SPP model, we compare it with two alternative planning models: a classical MRP model and a Myopic Requirements Planning (MyRP) model. This section describes these models.

We consider a *classical MRP model* that generates production plans under the assumption that, for each type i product, the lead time is a specified nonrandom constant L_i measured in terms of time periods, and its requirements R_{it}

are not random. The general MRP philosophy is to release quantities in each period that would cover the requirements in the next L_i periods. For simplicity, assume there are no auxiliary constraints on the release quantities.

Specifically, at the beginning of each time period, the system would perform the following steps for each type i product:

- Observe the production output from the previous period and the current WIP quantities $w_{i0}(k)$.
- Update the requirements based on new demand forecasts and the previous period output (increase or decrease future requirements by backlogged products or extra finished products, respectively, from previous period).
- Compute the current release quantities using the formula

$$x_{i1} = (R_{iL_i} - \sum_{k=1}^{M} w_{i0}(k))^+, \qquad i = 1, \ldots, I,$$

  where R_{iL_i} is the requirement for the next L_i periods.
- Release the quantities x_{i1} into the system for the current production period.

Although this model generates production plans dynamically, the release quantities do not depend on costs or QOS. Practitioners, recognizing that there are production uncertainties, might choose conservative lead times to try to ensure that requirements are satisfied on time with a high probability. For instance, one might set the lead time constant to be $L_i = \mu + \sigma$, when one believes the lead time to be a random variable with mean μ and standard deviation σ. However, conservative lead times result in higher holding costs for finished products.

We also compare the SPP model with a *Myopic Requirements Planning* (MyRP) model. We briefly describe the model here. For a more detailed description, see (Riaño et al. 2002). The MyRP model is a one-period look ahead model where, at the beginning of each period, the WIP and next period requirements are observed, and a manager releases enough products to meet the requirements with a desired probability.

The output distribution function of each period is modeled as a convolution of several binomial random distributions, and approximated by a normal distribution with respective mean and variance

$$\mu_i = x_{i1}F_i(1) + \sum_{k=1}^{M} w_{i0}(k)F_i(1;k), \tag{9}$$

$$\sigma_i^2 = x_{i1}F_i(t)\,[1 - F_i(1)] + \sum_{k=l}^{M} (w_{i0}(k)F_i(1;k)\,[1 - F_i(1;k)]\,. \tag{10}$$

Since this model is used only for comparisons, we assume that the requirements are not random. Then the QOS constraint (3) can be modeled as

$$\Phi\left(\frac{R_{i1} - \mu_i}{\sigma_i}\right) \le 1 - \alpha_{i1}, \qquad i = 1, \ldots, I. \tag{11}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

Consequently, the MyRP policy would be to choose the release quantities to be the smallest x_{i1} that satisfies (11).

In summary, the MyRP would operate as follows. At the beginning of each time period, the system would perform the following steps for each product i:

- Observe the production output from the previous period and the current WIP quantities $w_{i0}(k)$.
- Determine the requirements R_{i1} for the "next" period based on demand forecasts and the previous period output (increase or decrease the old requirements by backlogged products or extra finished products, respectively, from previous period).
- Release the quantities x_{i1} into the system for the current production period, where x_{i1} is the smallest quantity that satisfies (11).

The prime consideration here is the QOS constraint; the lead time distribution is used in a limited way for a one-period look ahead. In contrast, the MRP model does not use the lead time distribution, but implicitly attempts to satisfy the QOS by inflating the lead time. Neither model uses costs to determine release quantities.

5 SIMULATION STUDY

In order to evaluate the SPP procedure with the two other MRP-like control policies in an integrated simulation environment, a simulation model of a manufacturing network shown in Figure 2 was constructed. As the focus is on high-level planning, we use a single-stage lead time distribution to represent the time for several production stages in the multi-station production network.

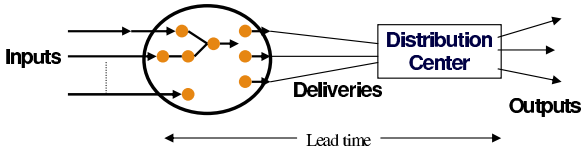

Figure 2: A Manufacturing Network

To implement the SPP procedure, the simulation model is interfaced with MOSEK (an optimization software) to solve the LP model for each period as shown in Figure 3. At the start of each time period of the simulation, the LP is solved for the optimal release quantities for the next T time periods based on the observed output of the previous period.

Figure 3 also illustrates how the MRP and MyRP models are integrated with the simulation model. The performance measure used for the comparison is the total average cost, which includes the late costs, early costs and in transit costs, for operating under each model's policy.

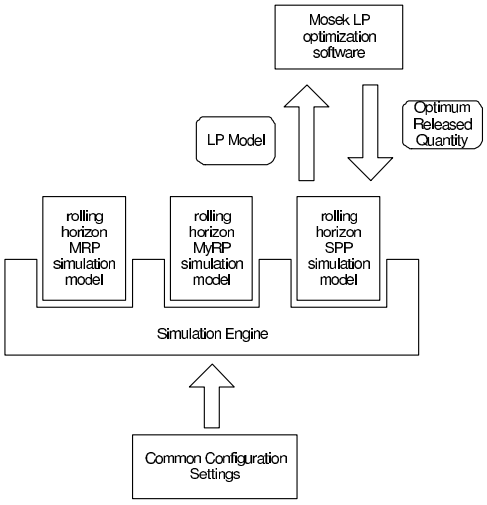

Figure 3: Integration of the Three Planning Models with the Simulation Model

We simulated the operations of the manufacturing network under the three planning models for a single product over $T = 50$ time periods. For each simulation scenario, we ran 50 replications. For each time period we simulated the completion times of the release quantities determined by the lead time and residual lead time distributions. A common lead time distribution assumption used in the literature (Sculli and Wu 1981) is the normal distribution. Here we consider a normal lead time distribution with mean 2 and variance 1, and a normal distribution with a larger mean 5 and variance 3. As the time periods are discretized, we also consider a discrete distribution with cumulative probabilities (.1, .3, .7, .9, 1) to test the distribution effects on the release patterns and costs.

To minimize distortions from initial settings like the initial WIP, we considered the first 20 periods as warmup, and only collected data on costs and observed QOS for the last 30 periods.

In Section 5.1, we first study the characteristics of the SPP model for various cost ratios and QOS levels. In Section 5.2, we study the release patterns of the three models (SPP, MRP, MyRP) and compare the total average costs of operating under each model.

5.1 Simulation Results for SPP Model

The operations of the manufacturing network was simulated with the SPP planning procedure for a variety of cost ratios and lead time distributions. Figure 4 shows the overall release quantities under the SPP procedure with various cost ratios for the different lead time distributions when the QOS level is set at 0.67. This level corresponds to meeting the requirements at least two thirds of the time.

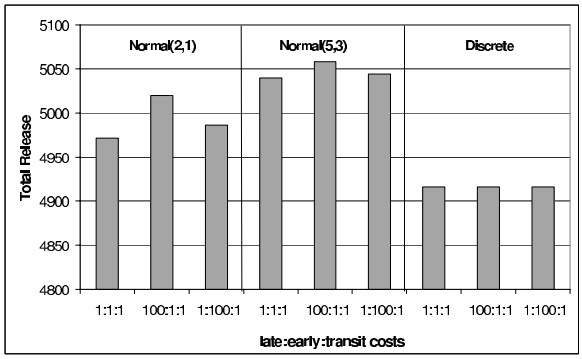

Figure 4: Total Release Quantity for Various Cost Ratios for the SPP model, where QOS = 0.67

The release quantities are higher when the late costs are high and lower when the early costs are high for the normal distributed lead times. This is intuitive as more is released when the late penalty costs is high and less is released when it is expensive to be early. The release quantities for the discrete distribution are similar for the various cost ratios. As the optimality of the solution to the LP can only be affected when the cost coefficients or 'production rates' are changed, in the case of the discrete lead time, the range of variation of the costs are still insufficient to change the optimal solution at each period to a different extreme point of the solution space. This indicates that in certain situations, the quality of service constraints are more crucial in determining the release quantities than costs.

Figure 5 plots the average cumulative release quantities for equal costs with varying QOS levels for the discrete lead time distribution. As expected, the average release quantities increase as the QOS level increases. Similar trends are seen for the normal(2,1) and normal(5,3) lead time distributions.

5.2 Simulation Results for SPP, MRP, MyRP Models

To compare the pattern of releases, Figure 6, Figure 7 and Figure 8 show the cumulative release quantity graphs for a single simulation run for the SPP model with equal costs, the classical MRP model and the MyRP models when the QOS level is set at 0.67. For the classical MRP model, the lead time is set to a constant $\mu + 1$ for the normal distributed lead times. This corresponds approximately to the 71^{st} and 84^{th} percentile of the normal(5,3) and normal(2,1) lead time distributions respectively. For the user defined lead time, the MRP lead time is set equal to 3. This corresponds to the 70^{th} percentile of the lead time distribution.

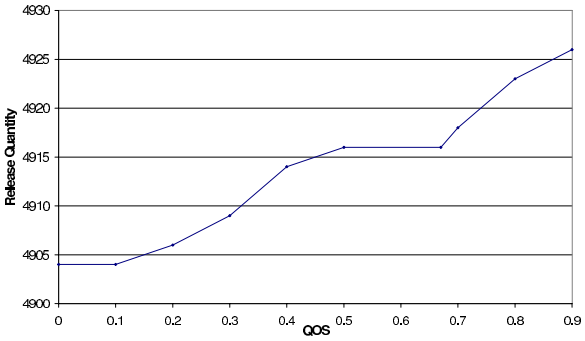

Figure 5: Discrete Lead Time: Average Cumulative Release Quantities for Period 50 for Equal Costs, at Different QOS Levels

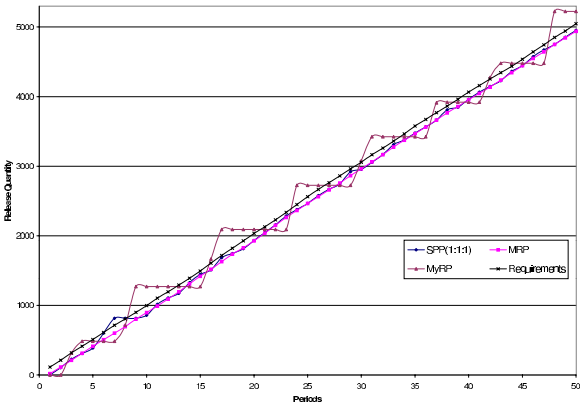

Figure 6: Discrete Lead Time: Cumulative Release Quantity for SPP Model, MRP Model and MyRP Model, where QOS = 0.67

The cumulative release quantities are smoother for the SPP model as compared to the MyRP model. The MyRP model does not account for the requirements for later periods and experiences large surges in release quantities when the WIP becomes insufficient to fulfill the requirements. The release quantities for the MRP model is parallel to the requirements, but shifted back to account for the constant lead time and initial WIP in system.

Next, we observe the total average costs for the various models. Table 1 shows the relative costs of the SPP model with respect to the MRP and MyRP models for different QOS levels. The SPP model has a much lower expected cost than the MyRP model (at least 25% less than the MyRP model, for the different distributions and QOS levels considered). This is because the SPP plan holds less finished inventory and WIP. The costs for the MRP model is comparable to the costs of the SPP model for the discrete distribution, where the lead time and variance is small. For the normal distributed lead times, the expected costs from the SPP plans is at least 10% less than the MRP plans. As the average lead times and variances become larger, without accounting

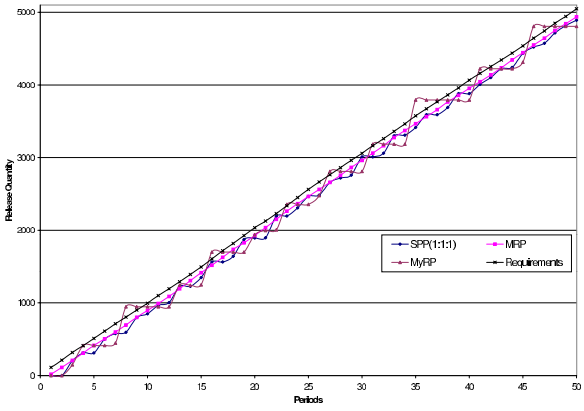

Figure 7: Normal(2,1) Lead Time: Cumulative Release Quantity for SPP Model, MRP Model and MyRP Model, where QOS = 0.67

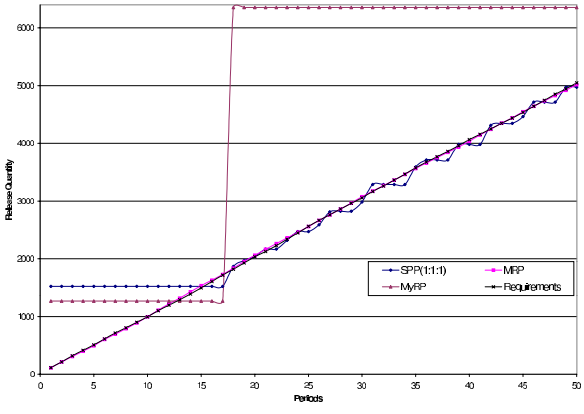

Figure 8: Normal(5,3) Lead Time: Cumulative Release Quantity for SPP Model, MRP Model and MyRP Model, where QOS = 0.67

for the uncertainty in the lead times, the costs for the MRP model becomes higher.

From the experiments conducted, we see that the SPP model outperforms the MyRP model in terms of costs. The releases for the SPP model are smoother than the releases of the MyRP model. The SPP model has a cost advantage over the classical MRP model as the lead times become larger and more uncertain, as it is more adaptive to the lead time uncertainties.

6 CONCLUSIONS

In this paper, we have described a dynamic stochastic optimization planning model that determines when to release raw materials into a production system or supply chain network. The model is applicable to a variety of systems whose lead times are random variables distributions of which can be estimated under “typical” operating conditions. As our approach is dynamic, it is flexible to various review policies, customer quality levels and costs. We have provided

Table 1: Relative Total Costs Comparison of SPP Model with Respect to MRP, MyRP Models ($\text{Cost}_{SPP}/\text{Cost}_{MRP}$) at Various QOS Levels

	User Defined		**Normal (2,1)**		**Normal (3,1)**		**Normal (5,3)**	
	MRP	MyRP	MRP	MyRP	MRP	MyRP	MRP	MyRP
$SPP_{.9}$	1.068	0.543	0.841	0.754	0.908	0.144	0.829	0.069
$SPP_{.67}$	1.018	0.574	0.800	0.756	0.897	0.157	0.847	0.149
SPP_0	0.997	0.460	0.788	0.570	0.856	0.149	0.770	0.327

a procedure for the practical implementation of the model in an extended simulation framework. We have also presented initial simulation results that show that the model is more realistic than MRP models and determines less costly production plans.

Future work includes the development of more general SPP models for production networks with multiple stations with several severs, explicit routing of products, and assembly of products. The lead times for these model must be formulated in more detail in terms of these network features, and the queueing delays depending on network loads. Successive approximation procedures developed in Riaño (2002) can be used to compute lead time distributions in these general cases, and applied in the dynamic optimization approach in the same spirit as the current SPP model.

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