Correspondence

A Decision Support System for Spare Parts Management in a Wafer Fabrication Facility

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***Abstract*—We present a decision support system for spare parts management in a wafer fabrication facility. The system is based on an analytical stochastic inventory model, which calculates the reorder level and quantity for each part to attain a specified service level. Results from our simulation study indicate that the policies suggested by the system either improve the service level or reduce the operating cost.**

I. INTRODUCTION

Unpredicted equipment downtime has long been recognized as a major source of uncertainty in semiconductor manufacturing facilities [3] and is very costly in terms of lost production. Eliminating excessively long failures provides the most significant improvement in system throughput and cycle time [4]. Lack of spare parts required for preventive and/or breakdown maintenance is an important cause of excessively long downtimes. However, inventory is expensive and can quickly become obsolete as equipment models change. For advanced manufacturing technologies, such as semiconductor wafer fabrication, the total investment in spare parts may easily amount to a significant fraction of the value of the equipment to be maintained. Therefore, management must balance the conflicting goals of minimizing inventory investment and maintaining high equipment availability.

This brief presents a decision support system (DSS) for spare parts inventory management carried out in an Intersil wafer fabrication facility. This spare parts management system plans inventory levels for a wide variety of equipment spare parts with widely varying demand patterns, lead times, and cost structures.

Considering the stochastic nature of the problem, a simulation-based tool would seem to be a natural solution method. However, the use and maintenance of such a tool would be time-consuming. We therefore developed a DSS based on an analytical inventory model that could be implemented in a spreadsheet on a personal computer. We examined a number of different inventory models from the literature and selected one of these to form the core of the DSS. This brief illustrates a case study in addressing the modeling and data analysis issues arising in a practical implementation.

A complete review of the relevant literature on stochastic inventory models can be found in [1]. A brief explanation of the data collection and analysis is presented in Section II. Section III describes the DSS, and Section IV gives the results of a simulation study used to evaluate its performance. Section V summarizes the study and presents conclusions.

TABLE I
SAMPLE SIZES FOR DATA SETS

Equipment Group	No. of Fast Movers	No. of Slow Movers
I	17	13
II	15	19
III	17	22
IV	16	16
V	6	11

II. DATA COLLECTION AND ANALYSIS

We reviewed available inventory level and annual usage data for the spare parts and classified the data based on specific tool groups such as photolithography and diffusion. Pareto analyses based on both annual usage and inventory costs were performed on each of these classes to see which items accounted for the majority of the annual spending or total inventory investment. Within each tool group, parts were classified as fast moving, slow moving, or bulk items. Based on management decision, fast moving parts are defined as those with an annual usage of four or more units, and slow moving parts with less than four units a year. The DSS ignores bulk items, which are purchased in large amounts and whose inventory levels are not monitored on a unit basis.

From five different tool groups, critical parts that account for 80% of the total dollar value of the annual usage were selected. For each tool group and part class the associated sample sizes are given in Table I. This provided us with a sample of slow and fast moving parts with relatively constant or highly variable lead-times and low and high unit costs. Data on the demand size and frequency were collected over the last 12 to 18 months.

III. MODELING AND ANALYSIS

A. Analytical Inventory Models

The majority of the analytical inventory models in the literature are based on the assumption that demand over lead time is normally distributed. However, our data did not support this assumption, especially for slow-moving parts. Spare parts demand tends to be skewed toward shorter lead times. We modeled the demand over lead time using a continuous gamma distribution. The parameters of this distribution were estimated empirically from the data.

Since our primary objective was reducing stock-outs, the accuracy of the reorder level s was more important than the accuracy of other parameters. Minimizing the inventory investment and the ordering costs were secondary goals. As the acceptable number of stock outs can be expressed in terms of service levels which could be incorporated into the calculation of the reorder level, we considered (r, Q) models, where r is the reorder level and Q the order size. We computed the reorder quantity assuming demand during lead time follows a gamma distribution and the reorder quantity using the single item economic order quantity (EOQ) method. For our experimentation, we have used service levels of 85, 90, and 95%.

The demand during lead time is estimated to determine the reorder level. As we assumed lead time to be a random variable, we needed to estimate the first two moments of the underlying distribution. We used the approach developed by Dunsmuir and Snyder [2] that distinguishes between the period demand D and positive period demand D^+. If π_D

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is the probability of a positive period demand, the mean μ_D and the variance σ_D^2 of period demand can be estimated as

$$\begin{aligned}\mu_D &= \pi_D \mu_D^+\\ \sigma_D^2 &= \pi_D \left(\sigma_D^+\right)^2 + \pi_D(1-\pi_D)\mu_D^+\end{aligned}$$

where the mean μ_D^+ and the variance σ_D^{+2} of the positive demand can be estimated using the positive demand data, and π_D using the data on the periods with transactions.

Given the first two moments of the period demand, the compound demand during lead-time distribution can be estimated using the convolution of the probability distributions for demand size and lead time. The parameters for the demand during lead time are:

$$\begin{aligned}\mu_{LTD} &= \mu_L \mu_D\\ \sigma_{LTD}^2 &= \mu_L \sigma_D^2 + \mu_D^2 \sigma_L^2\end{aligned}$$

where μ_L and σ_L^2 represent the mean and variance of lead time, respectively, and can be estimated using the lead-time data.

The calculation of reorder level is a straightforward cumulative probability distribution application for the gamma distribution. In calculating the order size, Q, we use the economic order quantity (EOQ) formula, which is

$$Q = \sqrt{\frac{2K\lambda}{iC}}$$

where

K ordering cost;
λ annual demand;
c unit cost;
i interest rate.

Using the reorder and order quantities, r and Q, respectively, the s and S quantities suggested are derived using the following expressions:

$$\begin{aligned}\text{Lower } s \text{ Suggested} &= \lfloor r \rfloor\\ \text{Upper } s \text{ Suggested} &= \lceil r \rceil\\ \text{Lower } S \text{ Suggested} &= \lfloor r \rfloor + \lfloor Q \rfloor\\ \text{Upper } S \text{ Suggested} &= \lceil r \rceil + \lceil Q \rceil .\end{aligned}$$

B. Decision Support Tool: Spreadsheet Application

The data requirements of the DSS are the system-dependent cost, part-dependent cost, and demand data. Once the data are entered into the spreadsheet, the reorder level is calculated and the system suggests minimum and maximum storage quantities and estimates the expected costs of the policy.

Part-dependent cost and demand data are the unit cost of the part, the number of issues per year, the average and standard deviation of the demand size per issue as well as the average and standard deviation of the lead time for the part. The unit cost for the part is obtained from the inventory tracking system assuming no volume discounts. For the demand, our time bucket is a month based on the preference of the spare parts manager. The number of issues per year is the number of months during the past year in which a request was placed for the part. For this piece of information, the amount of demand is irrelevant and all we need to capture is whether there was a positive demand during any given month. The average and standard deviation of the demand size similarly corresponds to the parameters of the monthly demand. For example, a part may have the following demand pattern: in January, a demand request of five units and, in May, demand requests of three, two, and three units may have been placed. Consequently, for this part, the number of issues is two and the average monthly demand is 6.5 units. Finally, the user has to specify a service level for the part.

The DSS suggests lower and upper bounds rather than exact minimum and maximum quantities. As we use the continuous gamma distribution to model the demand during lead time, the reorder level often turns out to be fractional. If the quantities are relatively large, rounding to the next greatest integer is a reasonable approximation. However, for a slow moving part whose reorder level lies in the interval [0, 1], the rounding decision is critical. If the unit cost of the part is high, rounding up adds substantially to the required inventory investment. However, by doing so, the service level for that part is increased considerably. For example, if the reorder level for the part is calculated to be 0.21 for a 95% service level, setting the reorder level to 1 may imply a theoretical service level as high as 99% assuming that the demand during lead time is positive. If the reorder level is rounded down, the investment requirement decreases, but so does the service level at an even faster rate. The DSS provides the user with lower and upper bounds, and leave the rounding decision to their discretion.

The DSS also presents the user with the economic implications of the alternative policies suggested using simple equations. As the user will round the fractional reorder level either up or down, the service level implied by the adopted policy will not necessarily be the same as the service level specified by the user. The implied service level sl_I is calculated using the cumulative distribution function of the demand over lead time. The expected number of orders is determined by dividing the annual demand by the order size $(\tilde{\lambda}Q)$. The expected annual holding cost is the inventory holding cost multiplied by the average expected inventory level $(h(r+Q)/2)$ and the expected average inventory investment is the unit cost multiplied by the average expected inventory level $(c(r+Q)/2)$.

C. Simulation Model

To evaluate the performance of the proposed DSS, a simulation model for the stock level for a single part was developed in SIMAN [6]. The demand process reduces the inventory level over time. An order is placed when the inventory level is reduced to or below the reorder level r. The inventory level is increased by an amount corresponding to the order quantity Q of the part, after a certain lead time associated with the order is incurred. If the inventory level falls below zero the order is expedited. If the supplier has the part, order arrives in 24 h at an additional cost over the standard order cost. However, for five percent of the expedited orders, the supplier also is out of stock and a longer lead time of 10 days is realized.

Each simulation run included 100 replications, each simulating the operation of the inventory system for the part for a year. The output from the simulation runs was used to estimate the probability of stock-out, the total down time per year, and the mean down time per stock-out. Statistics on the average inventory investment required and the annual ordering and holding cost were also collected to quantify the economic implications of the policy.

Statistical tests revealed that the exponential distribution could be used for the interarrival times of the demand, and we fit parameters using historical data. For demand size distributions, we derived empirical distributions since the demand patterns were highly variable across our sample of parts. In the historical data, the surges in demand representing periods when parts on all machines are changed during preventive maintenance were eliminated as outliers. As the preventive maintenance schedule and the spare parts needed for preventive maintenance are known ahead of time, these parts can be procured separately.

To define the inventory replenishment process, we had to fit distributions to lead times. There were discrepancies in the lead-time data and the variance turned out to be very high for various reasons. We used a triangular distribution to model the lead time as it was easier to obtain

TABLE II
RESULTS FROM SIMULATION EXPERIMENTS

		Deviation from Current Constant Lead-Time Case			Deviation from Current Actual Lead-Time Case		
Performance Measure	Part Class	SL 95%	SL 90%	SL 85%	SL 95%	SL 90%	SL 85%
Probability of a Stock-out	Fast Movers	-32%	6%	41%	-57%	-15%	17%
	Slow Movers	-81%	-68%	-47%	-89%	-68%	-55%
Total Down Time (hrs./yr.)	Fast Movers	-4%	43%	69%	-6%	53%	87%
	Slow Movers	-54%	-25%	2%	-55%	-10%	-2%
Average Down Time per Stock-out (hrs./stock-out)	Fast Movers	-17%	9%	28%	-23%	7%	68%
	Slow Movers	-47%	-21%	-2%	-45%	-18%	9%
Average Cost per Year	Fast Movers	-9%	-13%	-19%	14%	7%	2%
	Slow Movers	-13%	-27%	-31%	-13%	-19%	-25%
	All Parts	-11%	-20%	-25%	1%	-6%	-12%
Total Investment ($/yr.)	Fast Movers	5%	-12%	-29%	42%	17%	1%
	Slow Movers	152%	79%	40%	159%	106%	71%
	All Parts	45%	13%	-10%	74%	41%	20%

the shortest possible, most likely and longest possible lead-time figures from historical data.

IV. RESULTS

Simulations were made using the parameters suggested by the DSS as well as the current values that have been set by the system expert. Our data set consisted of 71 fast-moving and 81 slow-moving parts. For each part, we derived reorder quantities for service levels of 85, 90, and 95% under two different lead-time settings. Although the model is capable of handling stochastic lead times, we used a constant lead time of 0.5 months based on management discretion. Additional simulation experiments were made to assess the impact of stochastic lead times.

We made seven simulation runs for each part with the current settings as well as the six experimental settings. Table II presents the percentage deviation from the value of the performance measure under current parameters. A negative (positive) value corresponds to a reduction (increase). In terms of the stock-out probability, the DSS has the potential of improving the service level by 32% for fast movers and 81% for slow movers using constant lead time if service level is set to 95%. When the actual lead-time data are utilized, the improvements are much higher, which indicates that using the actual lead times improves the performance of the DSS.

The policies suggested by the DSS reduce the operating costs for the constant lead-time case for two reasons. By limiting the number of potential stock outs, the number of expedited orders is reduced, resulting in lower ordering costs. In addition, as the EOQ optimizes the tradeoff between the ordering and the holding costs, the inventory operating costs go down. When the actual lead time are used, however, the operating costs increase due to increased inventory levels for expensive items with long lead times. For example, consider a part with a lead time of three months and a unit cost of $5000. Keeping more stock to cover the expected demand during these three months instead of 0.5 months increases the holding cost for the part. Operating cost (ordering and holding costs) tend to decrease with service levels. This suggests that, as the service levels go down and stock levels are reduced, the inventory holding cost decreases faster than the increased ordering cost of expedited orders.

The policies suggested by the DSS increase the investment requirement, which clearly depicts the dilemma we have aimed to address. If investment requirement is used as the only performance measure for spare parts management, the information on service levels in terms of duration of the down time and stock-out probability are not taken into consideration, and fab performance might suffer if required spare parts are not in stock.

V. CONCLUSION AND FUTURE DIRECTIONS

We have demonstrated how existing inventory models in the literature can be used to develop a practical application. Rather than the normal distribution assumed for demand over lead time in much of the literature, the gamma distribution with its flexibility to assume different shapes and being defined for only positive values proved to be appropriate for the spare parts inventory problem considered. Both the system developer and the user have to be aware of the implications of the assumptions of the models. For example, the definition and interpretation of service level, fill rate, and stock-out cost in the context of spare parts management must be given some careful thought. The DSS developed here is user friendly in the form of a simple PC spreadsheet and allows practitioners to use operations research concepts easily and effectively.

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