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INVENTORY SURVIVAL ANALYSIS FOR SEMICONDUCTOR MEMORY MANUFACTURING

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ABSTRACT

The high variety of and intermittent demand for semiconductor memory products frequently limits the use of forecast error normalization in estimating inventory. Inventory turnover is a practical performance indicator that is used to calculate the number of days for which a company retains inventory before selling a product. Although previous studies on inventory level settings have primarily applied information regarding demand variability and forecast error, few studies have investigated the inventory turnover for inventory decisions. Inventory turnover data are time scaled, suited for a small sample, and right censored to fit the input of survival analysis. In this study, a model in which inventory turnover and survival analysis were integrated was developed to estimate the production inventory survival function used to determine inventory level. Data analysis results based on real settings indicated the viability of using inventory survival analysis to determine semiconductor memory inventory level settings.

1 INTRODUCTION

Rapid technological development and shortened product life cycles have created the risk of excess inventory and extensive inventory obsolescence in semiconductor memory manufacturing (Wu 2013). Semiconductor manufacturing is capital intensive, and manufacturers strive to increase productivity and enhance capacity utilization to retain capital effectiveness and competitive advantages (Chien et al. 2007). Practical supply chain models have indicated that allocating inventory to satisfy customers and improving capital utilization are crucial (Wieland et al. 2012, Degbotse et al. 2012) to maintaining reasonable inventory levels.

Demand uncertainty is vital to determining the inventory level. Numerous studies have focused on the accuracy of demand forecasting and setting the safety stock level under a rolling schedule. Applying lead time and order quantity as decision variables, Ben-Daya and Raouf (1994) proposed a model that uses various representations of the relationship between lead time crashing cost and lead time. Boulaksil et al. (2009) considered the problem of determining safety stocks for multiitem multistage inventory systems in which demand uncertainty was encountered and recommended applying the mean absolute deviation to compute forecast errors.

However, during practical work division, the sales unit typically forecasts demand, and the production unit mainly plans production and manages inventory. In this environment, inventory planners must address two challenges when maintaining safety stock level according to demand variation. First, the inventory planners rather than the sales unit must determine the demand distribution. Second, when the inventory planners calculate the demand, other units experience difficulty in accepting inventory level settings for going beyond a production unit's duties.

Most previous researchers have used the variation of demand or forecast error as parameters with which to construct safety stock levels (Graves et al. 1993). Because declining product demand leads to a loss of orders and high stock levels, examining the product life cycle of electronic components and adjusting stock levels accordingly to reduce overdue inventory costs is necessary (Solomon et al. 2000). Enns (2002) considered the effect forecast bias and demand uncertainty exert to adjust demand forecasting. However, in the high-tech industry, defining a standard forecast error when contending with hundreds or thousands of product types is difficult. Generally, the forecast error is defined as the difference between forecasting demand and actual demand, and is frequently used to determine a suitable safety inventory. However, the forecast error is not unit invariant and, therefore, cannot be used to compare products that have large and varying baseline demands.

In most demand-dependent production environments in which demand and procurement and manufacturing lead times vary, safety stocks are required to achieve reasonable service levels (Ruiz-Torres and Mahmoodi 2010). Two methods are used to set safety stocks: a quality-based method, which is used, for example, to adjust the forecasting demand according to the variation in historical demand data (most researchers employ this method), and a time-based method, which is applied to consider the demand and inventory information from planning periods and determine how current inventory levels can satisfy the future demand over the following days or months.

The inventory turnover, which is defined as the degree to which the current inventory level can satisfy the future demand in terms of days or months, is commonly used by semiconductor memory manufacturers to manage hundreds or thousands of product types. The inventory turnover provides a more intuitive viewpoint and an easier means for communicating. For example, an inventory turnover longer than 12 months indicates excessive inventory, whereas an inventory turnover shorter than one month typically suggests that the shortage risk necessitates an approximate 3-month average lead time of flash memory. The inventory turnover data on semiconductor memory products are time scaled, suitable for a small sample, and right censored to fit the survival analysis input. In this study, a model in which inventory turnovers are integrated with survival analysis was developed to estimate the production inventory survival function used to set the inventory level. An empirical study conducted using real settings collected from a semiconductor memory integrated device manufacturer (IDM) located in the Hsinchu Science Park in Taiwan investigated the viability of the proposed model.

The remainder of this paper is organized as follows: Section 2 reviews the fundamentals of inventory setting applied when demand uncertainties and forecast accuracy exist and describes the inventory survival analysis (ISA). Section 3 details the empirical study conducted using real data collected from a semiconductor manufacturing company in Taiwan. Lastly, Section 4 summarizes the results and contributions of this study and describes future research directions.

2 FUNDAMENTALS

2.1 Inventory Turnover

The parameters $J_\varepsilon(t)$ and $D(t)$ are the inventory level and actual demand at time t, respectively. Given a confidence level $1-\alpha$ and the Gaussian quantile Z_α, the safety stock is determined using (1) and according to the normality assumption. For products with longer life-time cycles, the unknown mean function $D(t)$ and uncertainty ε can be precisely estimated based on a large number of historical data.

$$J_{\varepsilon}(t) = D(t) + Z_{\alpha}\varepsilon \tag{1}$$

However, for products with shorter life-time cycles, the small sample size results in a large standard error when estimating $D(t)$ and ε. Two approaches can be employed to estimate $D(t)$. The professional experience of the salesperson can be used, or $D(t)$ can be assumed to be a constant and estimated according to the sample mean based on the previous observation at t.

$$\hat{D}(t) = \frac{1}{t-1}\sum_{i=1}^{t-1} D(i) \tag{2}$$

Table 1: Conventional criteria to evaluate forecast error.

Absolute error			**Relative error**	
Bias	Mean squared error	Mean absolute distance	Mean absolute percentage error	Symmetric mean absolute percentage error
$\dfrac{\sum_{i=1}^{t-1}\left(\hat{D}(i)-D(i)\right)}{t-1}$	$\dfrac{\sum_{i=1}^{t-1}\left(\hat{D}(i)-D(i)\right)^2}{t-1}$	$\dfrac{\sum_{i=1}^{t-1}\left\lvert\hat{D}(i)-D(i)\right\rvert}{t-1}$	$\dfrac{\sum_{i=1}^{t-1}\left\lvert\dfrac{\hat{D}(i)-D(i)}{D(i)}\right\rvert}{t-1}$	$\dfrac{\sum_{i=1}^{t-1}\left\lvert\dfrac{\hat{D}(i)-D(i)}{\left(\hat{D}(i)+D(i)\right)/2}\right\rvert}{t-1}$

After $D(t)$ is estimated, ε can be estimated using the following equation:

$$\hat{\varepsilon} = \frac{1}{t-1}\sum_{j=1}^{t-1}\left(\hat{D}(i) - D(i)\right)^2 \tag{3}$$

Table 1 lists various conventional measurements used to evaluate the forecast error. Using absolute errors is inappropriate when comparing products that have large, varying baseline demands. For example, consider a salesperson who predicts the demand for the following 4 months at the beginning of the first month (Table 2, third row); however, by the end of the first month, he or she knows that the prediction was underestimated by 20 products and, therefore, updates the following 4-month predictions (Table 2, sixth row). At the end of the second month, the salesperson realizes that the prediction was again underestimated by 20 products. Although the two forecasts resulted in the same bias, the error rate of the first was 20% and that of the second was near 0.2%. The relative error generally is more appropriate for evaluating the forecast error. However, the relative error may vary when the denominator is zero; this variation occurs when estimating the inventory of products that are subject to a seasonal effect. To objectively measure the forecast error, the inventory turnover was applied in this study.

Inventory turnover represents the actual demand that must be fulfilled after a number of forecast periods. Let $\hat{D}(t)$ denote the salesperson's forecast demand, T_1 denote the maximal time before $\hat{D}(t)$ fulfills $D(t)$, and T_2 denote the proportion of the remaining demand to the T_1+1 forecast at time t; T_1 and T_2 can be formulated as (4) and (5), respectively.

$$T_1 = \arg_{T} \max_{T \ge 0}\left[\sum_{j=t}^{t+T}\hat{D}(j) < D(t)\right] \tag{4}$$

$$T_2 = \frac{D(t) - \sum_{j=t}^{t+T_1}\hat{D}(j)}{\hat{D}(T_1+1)} \tag{5}$$

Table 2: Comparison between inventory quantity and inventory turnovers.

Month	1	2	3	4	5
Actual demand	100	10000	100	70	130
Forecast at month 1	80	10100	70	20	
Inventory quantity	-20	100	-30	-50	
Inventory turnovers	1 + 20/10100	0+10000/10100	2^++0	1^+ + 0	
Forecast at month 2		9980	200	40	80
Inventory quantity		-20	100	-30	-50
Inventory turnovers		1 + 20/200	0 + 100/200	1 + 30/80	1^+ + 0

The inventory turnover is expressed as

$$J_\tau(t) = T_1 + T_2 \tag{6}$$

Unlike the relative error listed in Table 1, inventory turnover equals 1 when the forecast is accurate. Overestimation and underestimation cause inventory turnover to be lower than and greater than 1, respectively.

In the aforementioned example, the salesperson underestimates the first demand; thus, $T_1 = 1$ in both cases. The remaining demands require 20/10100 and 20/200 of the subsequent forecasts to be fulfilled. Therefore, the inventory turnover is 1.002 and 1.010 for the first and the second forecasts, respectively. Thus, using the inventory turnover as an error criterion is appropriate because it does not fluctuate with the baseline demand.

2.2 Product Limit Estimator

In a make-to-stock industry, salespeople must predict a fixed number, n, of future demands. Therefore, the value of t in T_1 and $J_T(t)$ may not be close n. In the aforementioned example, because the salesperson provides 4-month predictions, $T_1 \le 4$. For the final prediction at the first month, T_1 and $J_T(t)$ are both greater than 1 and are not explicit numbers. Unlike data that provide complete information, these data provide partial information and are therefore incomplete data or, more precisely, right-censored data. In Table 2, N^+ denotes the censored observation, indicating that T_1 is greater than N. In these observations, $T_2 = 0$.

Right-censored data are frequently applied in biological and reliability research. For example, to determine the survival time of a patient with cancer, the survival function can be expressed as

$$S(t) = \Pr(T > t) \tag{7}$$

where T is the patient survival time. In other words, the probability that the patient will survive after time t is estimated. Equation (7) can be estimated by using the empirical distribution function $\hat{F}(t)$:

$$\hat{S}(t) = 1 - \hat{F}(t) = \frac{1}{n}\sum_{i=1}^{n} I(T_i > t) \tag{8}$$

Asymptotic properties of (8) are discussed by van der Vaart (1998). However, contact may be lost with various patients during the experiment. The visit records indicated that the survival time is longer than a period and right-censored data are obtained. Right-censored data are typically recorded as (T_i, δ_i), where T_i is the time when patient i leaves the experiment and δ_i = 1 if T_i is complete; otherwise, δ_i = 0. $(T_{(i)}, \delta_{(i)})$ denotes the ordered T_i with the corresponding δ_i. Kaplan and Meier (1958) suggested estimating (7) by using a product-limit estimator:

$$\hat{S}(t) = \prod_{t_{(i)} < t} \left(\frac{n-i}{n-i+1} \right)^{\delta_{(i)}} \tag{9}$$

Because (9) is a step function, it may not achieve the exact confidence level.

2.3 Inventory Survival Analysis

In this study, ISA was used to ascertain the inventory level according to a user-specified confidence level. The procedure is described as follows:

Step 1: The lead time k was determined according to the manufacturing cycle time. Although using a lower k typically results in a more accurate estimate of $D(t)$, the manufacturer may not achieve the inventory level on time. Because using a greater k increases the difficulty of estimating $D(t)$, a higher inventory level is often obtained.

Step 2: The confidence level α is set. The confidence level represents the probability that the inventory level will fulfill the actual demand after time k. Hence, using a greater α results in a higher inventory level, and vice versa.

Step 3: The inventory turnover is computed. According to Section 2.1, historical data is expressed as (T_i, δ_i).

Step 4: The product-limit estimate is computed. Fig. 1 depicts the estimated distribution function, which equals 1-$S(t)$. When the inventory level is one month, the probability that the actual demand will be fulfilled is 60.53%. If the confidence level is set between 90% to 90.13%, then the inventory level should be set to 5.43 months.

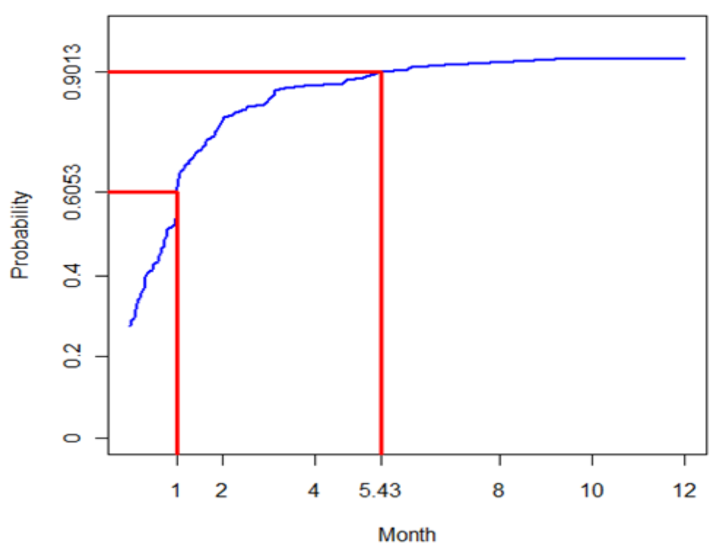

Figure 1: Product-limits estimate.

3 EMPIRICAL STUDY

An empirical study was conducted using real settings obtained from a semiconductor memory IDM located in the Hsinchu Science Park, Taiwan, to demonstrate the viability of the proposed model. The product dataset contained action demand data from January 2011 to December 2011 and four 12-month action demand rolling forecasts (Table 3) predicted by the salesperson. More complete approaches that incorporate with seasonal factors, market growth rates, prices, repeat purchases, technology substitution, and technology diffusion can be found in Chien et al. (2010). Because of limited space, only five products are described as examples in this paper. Incomplete product data entries were completed with zeros. For example, Product P had no actual demand data (i.e., an empty entry) in January and June 2011 when no shipments occurred (no actual demand recorded) within the period; thus, zero values were inserted to complete the demand data.

The input data were then transformed into inventory turnovers and possible censored records. According to one product, for each one-month actual demand, the inventory turnover was calculated using the value obtained in (6) as the number of accumulated forward-looking months of forecast demand that could satisfy the actual demand. When the actual demand was zero, the inventory turnover was set to zero, indicating that zero months of accumulated forward-looking forecast demand could satisfy the actual demand. For example, the inventory turnover in January was zero (Table 3), and the inventory turnover in February was 2.2, considering one full month for the first-month forecast (zero), another full month for the second-month forecast (5,000), and 0.2 month for the third-month forecast (1,000 out of 5,000). The inventory turnover in March was 5. The inventory turnover data from the first 3 months were complete. However, the inventory turnover in April was 12 and right-censored ($\delta_i = 0$) because the actual demand (8,000) could not be satisfied by the forward-looking 12-month forecast demand. The ISA was effective for situations in which the actual demand was zero or both the actual and forecast demand were zero, and the mean absolute percentage error and the symmetric mean absolute percentage error were not clearly defined.

Regarding the paired inventory turnovers and censored data ($\delta_i = 0$ or $\delta_i = 1$), records were sorted in ascending order according to inventory turnover for each product (Table 4). Step 4 was then performed to compute the Kaplan-Meier product-limit estimate. Table 5 lists the obtained confidence levels with the corresponding inventory turnovers. The inventory planners can specify their own confidence levels to determine the amount of inventory turnover and, accordingly, prepare the inventory for future demand. For example, if the confidence level of Product X is set as 0.6, then 78% of the forecast demand should be prepared for inventory. In other words, when ISA is used, preparing sufficient or excessive inventory is unnecessary if the forecast is overestimated. If the confidence level of Product X is set to 0.7, then 102% (1.02) of the forecast demand should be prepared for inventory, implying that the extra 2% of the forecast is prepared as safety stock. In practice, the forecast accuracy may vary according to the product. The forecast of Product W was underestimated, yielding a low inventory turnover of 0.96, even though the confidence level was set to 0.8.

The Kaplan-Meier product-limit estimate is convenient for use in inventory planning because it is a single variable that reflects the time dimension and forecast accuracy. If the turnover is 1.1, then the inventory planner prepares an extra 10% of inventory according to the forecast. Lead times can be considered by shifting inventory preparation along the time horizon in advance.

Table 3: Illustrative actual demand, rolling forecast by the salesman, and the inventory turnovers

Product P	Jan.	Feb.	March	April	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.	Jan.	Feb.	March
Actual demand	0	6,000	6,000	8,000	2,000	0	1,700	1,000	6,000	1,200	0	0	-	-	-
Forecast at month 1	1,760	0	5,000	5,000	1,056	1,056	1,060	1,060	1,060	1,560	1,060	1,056	-	-	-
Forecast at month 2	-	0	5,000	6,000	1,156	1,150	1,750	7,560	1,560	1,760	1,750	1,750	1,560	-	-
Forecast at month 3	-	-	1,200	1,200	1,200	1,200	1,200	1,040	8,000	1,200	1,000	6,000	5,000	9,600	-
Forecast at month 4	-	-	-	0	0	200	500	2,000	0	0	200	700	200	0	0
Inventory turnovers	0.0	2.2	5.0	12.0	…	…	…	…	…	…	…	…	…	…	…

Table 4: Illustrative inventory turnovers and censored Data

Product	Sequence	Inventory turnover	δ_i
A	1	0.00	1
	2	0.00	1
	3	0.01	1
	4	0.31	1
	5	4.00	1
B	1	0.78	1
	2	0.98	1
	3	1.02	1
	4	2.60	1
	5	3.15	1
	6	4.67	1
	7	12.00	0
	8	12.00	0

Table 5: Mapping inventory levels with confidence levels via the estimated distribution function

	Confidence Level			
Product	0.6	0.7	0.8	0.9
U	0.00	0.00	12.00	12.00
W	0.00	0.50	0.96	2.60
X	0.78	1.02	2.60	3.15
Y	1.00	1.00	1.00	1.68
Z	0.00	0.00	0.00	12.00

4 CONCLUDING REMARKS

In this study, novel applications of survival analysis were proposed to address uncertain inventory settings when forecasting is inaccurate. Inventory planners can specify their own confidence levels (or service levels) to determine corresponding inventory turnover and inventory levels by using Kaplan-Meier product-limit estimation, which is simple and effective even when actual demand is zero or the demand level substantially differs among products. The proposed ISA can be applied to manage temporal data that are derived from small samples and are right censored. The results suggested that using ISA to facilitate inventory setting in the semiconductor manufacturing industry is feasible.

Future research may consider additional external factors that might affect inventory settings, and multivariate analyses can be conducted to determine the inventory setting policy. In addition, hypotheses tests, such as the log-rank test, can be applied in conjunction with domain knowledge to facilitate product grouping and reduce the complexity of inventory item management, thereby enhancing the effectiveness of inventory planning.

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