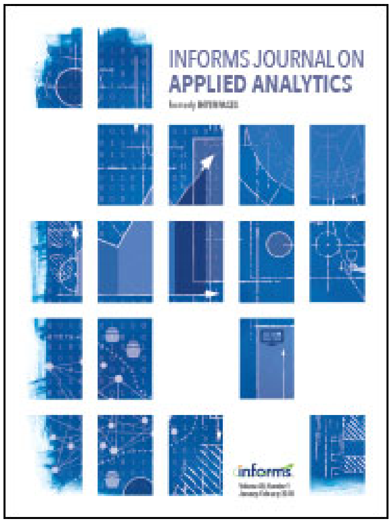

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Setting Safety-Stock Targets at Intel in the Presence of Forecast Bias

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Inventory target setting within Intel's embedded devices group historically consisted of management-determined inventory targets that were uniformly applied across product families. Achieving and maintaining these inventory targets at the individual product level proved to be a difficult task. To better align inventory resources and improve customer-service levels, Intel employed a multiechelon inventory optimization (MEIO) model to set inventory targets. However, the company could not implement the model's initial recommendations because of the presence of bias in the sales forecast data. Managing the forecast bias by directly modifying the raw sales forecast data was not an option because Sales and Marketing controlled and loaded the data into the manufacturing resource planning (MRP) system before the planning organization received it. Therefore, the average forecast demand, with its bias present, was already in the system; the only adjustment that the planning organization could make was to change the inventory target. This paper describes the inventory optimization problem in Intel's embedded devices group and the adjustment procedure that we developed to produce appropriate inventory targets in the presence of forecast bias.

Key words: forecasting: applications; industries: computer/electronic; inventory/production: applications, multiechelon safety-stock optimization.
History: This paper was refereed.

High overall inventory levels and inconsistent adherence to customer-service level targets for two product families within Intel's embedded devices group led Intel's planning organization to explore new inventory management techniques to reduce inventory costs, while simultaneously raising customer-service levels. Prior to 2004, the existing inventory levels for both product families were significantly above the management-dictated targets (Figure 1).

In Intel's embedded devices group, a product family consists of multiple, unique finished-goods stock-keeping units (SKUs) that share a common design but are differentiated throughout the manufacturing process. We modeled and analyzed two such product families for this paper.

In 2004, Intel introduced a multiechelon inventory optimization (MEIO) tool to optimize inventory targets across the end-to-end supply chain. Initial models for the two product families produced counterintuitive results with respect to safety-stock targets. Namely, the models recommended holding significantly more inventory than Intel currently deployed in the supply chain. These counterintuitive results led to a thorough examination of Intel's planning process and the identification of several problems. First, the sales forecasts for virtually all the SKUs exhibited significant bias. Second, this biased sales forecast was loaded into the planning system in the form of the planned demand for future periods before the planning organization set the inventory targets. Third, the MEIO model assumed that the demand inputs were unbiased.

The standard approach to address bias, e.g., as in Makridakis et al. (1998), consists of transforming the raw sales forecast data to remove the bias from the source data. However, given Intel's planning process, this approach was not feasible; the planning organization has responsibility for setting inventory targets; however, it does not have control over the sales forecast because the Sales and Marketing group loads

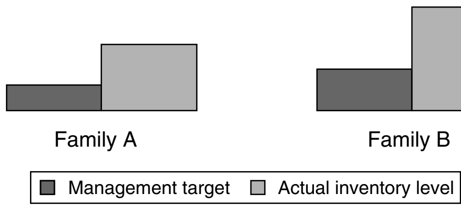

Figure 1: Product-family inventories were well above management-determined targets.

the forecast into the MRP system before the planning organization sets inventory targets. Therefore, when considering how to parameterize the inventory model, the planning organization needed to take into account that it would not have control over the average demand loaded into the MRP system.

This paper presents the solution that Intel's planning organization developed to determine SKU-level inventory targets in the presence of forecast bias by modifying the estimate of the standard deviation of forecast errors.

Intel's Traditional Method of Setting Inventory Targets

The two product families that we cover in this paper comprised 44 active SKUs with an aggregate annual volume in the millions of units. The traditional process for setting inventory targets establishes a weeks-of-inventory (WOI) policy by product family, where one week of inventory represents average future weekly sales. Although different product families may have different WOI targets based on the product-family's management-determined strategic importance or its stage in the life cycle, all SKUs within the product family share the same WOI target.

The supply chain for each product family consists of four echelons with multiple physical locations that comprise a worldwide factory and warehouse network. The stages of the supply chain include manufacturing sites for die fabrication and sorting (F/S), which supply a semifinished goods (SFG) warehousing echelon, followed by assembly and testing (A/T), and then finished-goods central warehousing (CW), which serves end-customer demand. In general, F/S and A/T locations never hold inventory; instead, they ship products to downstream adjacent echelons as soon as the items complete processing. Traditionally, Intel set inventory targets independently for the CW and SFG warehousing stages based on management objectives. Figure 2 presents a detailed representation of the four-echelon supply chain at the SKU level for one product family. By echelon, the supply chain map in Figure 2 has six stages in F/S, nine stages in SFG, 58 stages in A/T, and 41 stages in CW. The second product family's supply chain is similar in both echelon structure and number of stages. In all, the MEIO model generated inventory targets for approximately 100 SKU locations.

The planning organization monitors inventory levels weekly; a major reset, which is driven by a new

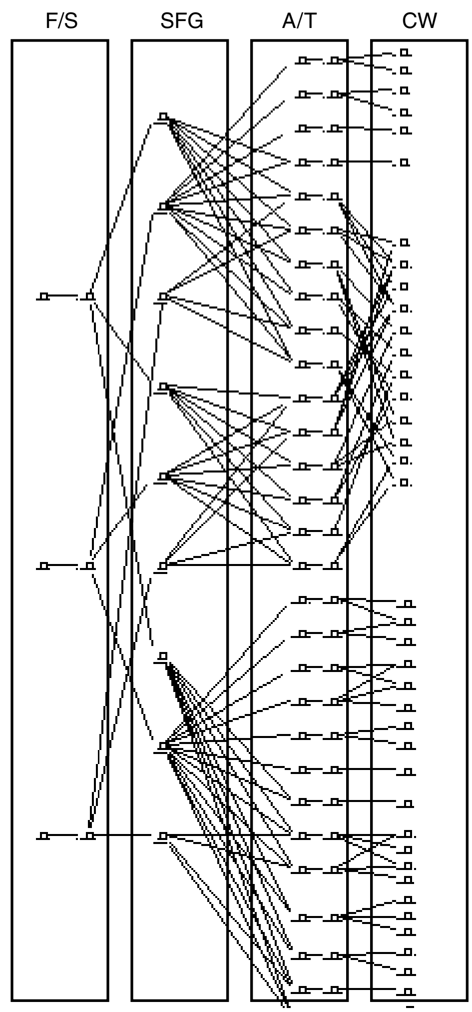

Figure 2: This graph depicts the actual multiechelon inventory optimization model for all SKUs within one Intel product family.

forecast that the Sales and Marketing group provides, occurs on a monthly basis. Based on the new demand information, the monthly planning process resets the forward-looking demand at the SKU-location level. This reset then modifies the current inventory target, which feeds an Intel-developed advanced-planning and scheduling (APS) optimizer that minimizes production costs, lost-sales costs, and costs for deviating from the inventory targets. The APS output is the constrained production and inventory plan, which constitutes the finalized factory schedule. Planners can also make weekly adjustments to the factory schedule in cases where either the actual factory output or the realized customer demand differs significantly from the monthly plan.

Improving Intel's Approach

Although operating parameters, such as throughput times and yields, are essentially identical within a product family, customer demand and forecast accuracy differ significantly by SKU. Coupled with blanket inventory targets assigned at the product-family level, it was common for some SKUs to regularly run low on inventory, while others had an abundance of inventory on hand.

Demand Characterization

At Intel, the demand characterization is the most significant input in determining safety-stock levels. In fact, the required safety stock due to demand variability alone typically accounts for the majority of all on-hand inventory. Because the specifics of the MEIO tool are not relevant to the impact of forecast bias, we exclude a discussion of the specifics of the tool's functionality, and instead consider the simplest demand characterization. At Intel, demand per period for each SKU is characterized by an average and standard deviation, denoted as μ and σ, respectively. For a given service level α and net replenishment time τ, the expected base-stock inventory level at a stage is then

$$\tau\mu + F^{-1}(\alpha)\sigma\sqrt{\tau}, \tag{1}$$

where $F^{-1}(\,)$ is the inverse Normal cumulative distribution function (CDF). The expected safety-stock target is then

$$F^{-1}(\alpha)\sigma\sqrt{\tau}. \tag{2}$$

There are two common approaches to characterize the μ and σ that populate (1). The first approach relies entirely on the actual historical demand to calculate an average and standard deviation of historical demand. This approach works well when demand is stationary or the forecast predicts future requirements less accurately than the demand history. The second approach uses the forecast and actual demand history to calculate how the forecast deviates from the actual demand. At Intel, products often have attributes, e.g., seasonality and product life cycles, which affect the average demand. Therefore, the second method is almost always the correct one to use. A sales forecast captures these deviations better than simply looking at past demand. This was true for the SKUs in this paper.

While statistics textbooks, including Brown (1959), define several methods for calculating the standard deviation of forecast errors (SDFE), the MEIO team used the standard formula in Equation (3) for each SKU:

$$\hat{\sigma}_{\mathrm{SDFE}} = \sqrt{\frac{\sum_{i=1}^{n}(F_i - D_i)^2}{n-1}}, \tag{3}$$

where n is the sample size, F_i denotes the forecast for demand in period i and made in period $i-1$, D_i denotes the actual demand in period i, and $\hat{\sigma}_{\mathrm{SDFE}}$ denotes the estimated SDFE. To test for bias, we calculated the relative forecast accuracy for each SKU by computing the ratio in Equation (4) in each period:

$$\theta_i = \frac{F_i}{F_i + D_i}. \tag{4}$$

For a given SKU, a time series of θs centered on 0.5 indicates unbiased forecasting. Figure 3 shows the results for 12 months of data for all 44 SKUs.

The histogram on the right side of Figure 3 demonstrates that SKU-level forecast error exhibits an overall positive bias. We also refer to positive bias as overforecasting; it occurs when an SKU's forecast in a given period is greater than the actual demand that materializes during that period. The x-axis on the contour plot is a measure of the size of an SKU's forecast in a given period relative to the SKU's maximum forecast. The contour shows that as forecasts grow relatively larger, a greater magnitude and likelihood for positive bias exists.

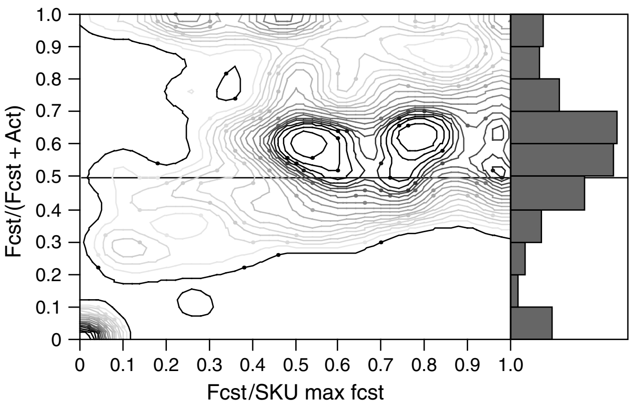

Figure 3: The product-family θ distribution histogram demonstrates clear bias to overforecasting. In addition, the larger the SKU's relative forecast, the more likely that there will be bias toward overforecasting.

Validating MEIO Results (Without Forecast Bias Compensation)

To assess the validity of using the scientifically derived safety-stock quantity from Equation (2) coupled with the SDFE estimate from Equation (3), we compared the MEIO targets against historical data. Intuitively, safety-stock buffers against the discrepancy between the sales forecast and actual demand; therefore, the safety stock required should bear some relation to the frequency and severity of underforecasting occurrences. Underforecasting is a situation where the actual demand exceeds the sales forecast. But as Figure 4 depicts for a typical SKU in this

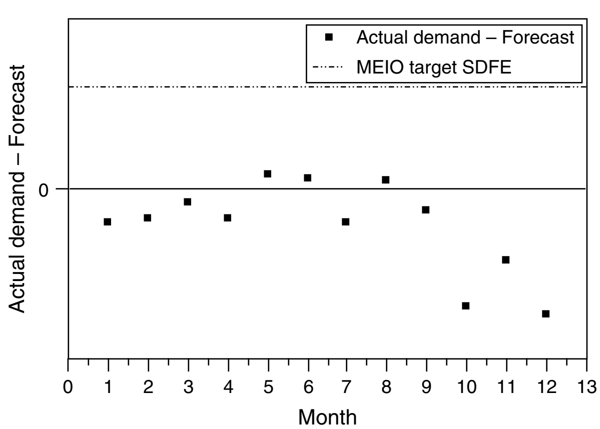

Figure 4: This graph shows a historical snapshot of one SKU's forecast accuracy residuals and suggested MEIO safety stock based on SDFE as computed in Equation (3). The suggested safety stock was considerably more than Intel ever needed to meet underforecasts.

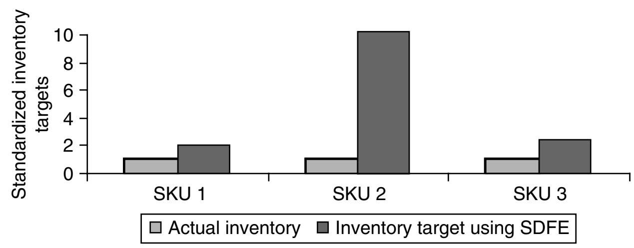

Figure 5: Inventory targets that the MEIO model generated using the SDFE as computed in Equation (3) were significantly higher than those of the products known to carry too much inventory.

validation exercise, when we compare product forecasting history with the MEIO-generated target, many SKUs were being instructed to hold significantly more inventory than the maximum underforecast that the SKU had ever experienced.

Further validation with product planners showed that side-by-side comparisons of current state inventory versus the MEIO inventory targets contradicted the product knowledge of the planning group. SKUs that were already known to carry significant excess inventory were instructed to hold even more inventory (Figure 5).

After validating the model's structure and other data inputs, we found that the root cause for the unrealistic safety-stock levels was the use of the variables in (2) to set safety-stock targets by using Equation (3) to calculate the SDFE in the presence of forecast bias. From (1), it is apparent that a forecast that exhibits positive bias will bring in too much pipeline stock, which will then sit in on-hand inventory. Therefore, the outcome of the validation exercise was a clear demonstration that the planning organization needed to consider forecast bias when setting safety-stock targets.

Addressing Forecast Bias

The standard approach to eliminate forecast bias is to directly modify the raw sales forecast data to eliminate the bias at its source. Textbooks, such as Crum and Palmatier (2003), treat this from a managerial perspective; textbooks such as Franses (1998) and Montgomery et al. (1990) treat it from a mathematical perspective where the outliers can be detected and removed. However, this approach was not feasible at Intel because the planning organization did not load the forecast into the MRP system. Therefore, even if the planning organization could remove bias from the forecast, the expected demand plan in the MRP system would continue to be populated with the biased data. Reengineering the planning process to eliminate forecast bias at the root source was infeasible within the project timeline.

In effect, the planning organization was left to set safety-stock targets using (2) with knowledge that the mean demand as specified in (1) exhibited bias. This required that the group modify the parameter inputs in (2) to remove the impact of the forecast bias without changing the mean demand produced by the MRP-loaded forecast. While the planning group could accomplish this by either modifying the service level α or the calculation for SDFE, it decided to modify the SDFE. To do this, we consider the distribution of forecast errors from the event-quantiles perspective, which is the percentage of occurrences for each error measurement. An estimate for the SDFE can then be backed out of the quantile value where the quantile value equals the desired service level. Stated a different way, this approach takes as input the raw sales forecast data and a desired service level. It then finds the underforecast quantile that aligns with the service level and uses the quantile to calculate an estimate for the SDFE that will serve as an input to (2), producing an expected inventory level that covers the underforecast quantile.

As an example, consider a monthly forecasting process, as Figure 6(a) depicts, with a distribution of forecast errors characterized as Normal(0, 1,000). We assume that the target service level is 95 percent. In Figure 6(a), −1,645 corresponds to the point where the cumulative distribution function equals 0.05.

Figure 6(b) graphs a Normal(1,000, 1,000) distribution and −645 corresponds to the cumulative distribution function of 0.05. If the distribution in Figure 6(b) is describing forecast error for an SKU on a monthly basis, on average, the forecast is 1,000 units too high with a 1,000-unit standard deviation. In this Normal(1,000, 1,000) setting, the SKU's actual demand will exceed its forecast in a month by more than 645 units only 5 percent of the time.

If we are confined to (2) to set the safety-stock target and the forecast error profile is Figure 6(b), then we need to modify the calculation of SDFE to net out

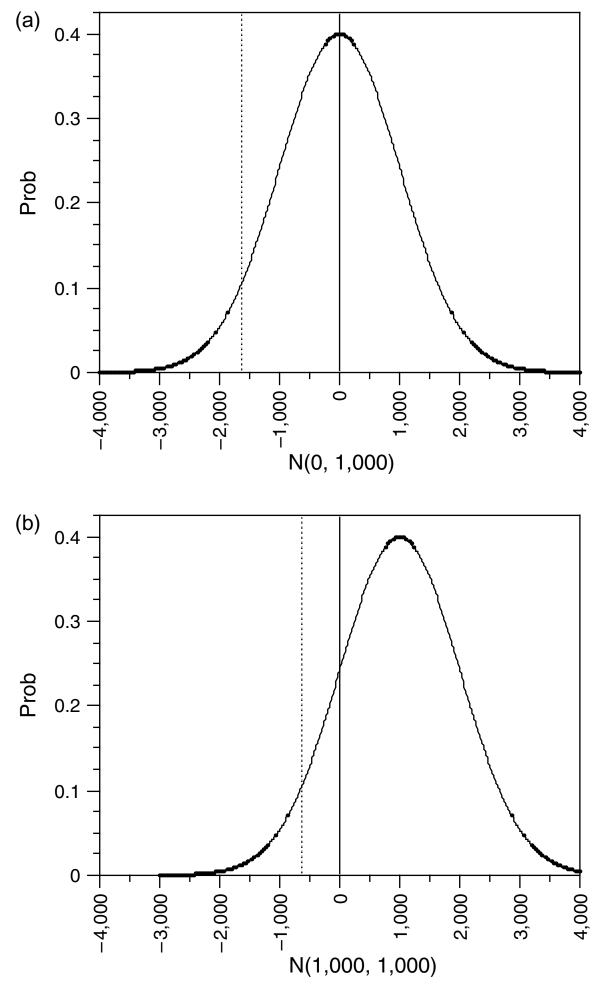

Figure 6: We plotted two normal distributions, N(0, 1,000) **and** N(1,000, 1,000)**, to demonstrate the point in each distribution where 95 percent of the probability lies to the right.**

the forecast bias. In particular, we can calculate this modified SDFE, denoted $\sigma^{Modified}$, as

$$\sigma^{Modified} = \frac{\mu}{F^{-1}(1-\alpha)} + \sigma, \tag{5}$$

where σ is calculated from Equation (3) and $1-\alpha$ is the unfill rate of one minus the service-level target α. In the Normal(1,000, 1,000) setting, the modified estimate of SDFE is

$$\sigma^{Modified} = \frac{1{,}000}{F^{-1}(1-0.95)} + 1{,}000 \approx 392.$$

For a forecast that is, on average, biased 1,000 units high and of a service level of $\alpha = 95$ percent, the appropriate estimate of the SDFE to populate (2) is 392, not 1,000. This foundation is the basis for Equation (6), a revised approximation of the SDFE that is based on the relative forecast accuracy from a product's sample history:

$$\hat{\sigma}^{Modified} = \max\left\{\frac{(1-\theta_\beta)/\theta_\beta - 1}{t_{\beta,\,df}}\mu,\, 0\right\}, \qquad (6)$$

where $\beta = 1 - \alpha$, θ_β denotes the quantile point corresponding to β from the distribution of θs calculated in Equation (4), $t_{\beta,\,df}$ is the student-t distribution with a cumulative density of β and degrees of freedom coming from the number of historical points to draw from, and μ is the average demand. $\hat{\sigma}^{Modified}$ is bounded below at zero. The enforcement of this bound arises when there are no past occurrences of an underforecast or when a service level is selected that is equal to or less than the proportion of overforecasting occurrences. Appendix A presents a numerical demonstration of Equation (6); Appendix B presents an additional enhancement to the approximation that adjusts for the SKU's demand volume.

If θ's distribution is unbiased, then $\hat{\sigma}^{Modified}$ from Equation (6) converges to the SKU's true SDFE from Equation (3) as the degrees of freedom increase. Therefore, as forecast accuracy improves, the use of Equation (6) does not need to change because it will converge with a slight lag to the SDFE.

Testing the Modified SDFE Approach

To compare the relative efficiency of the modified SDFE approach, we examine the impact to expected inventory levels for three approaches to a systematically biased forecast where the true demand variability is independent and identically distributed (i.i.d.). The baseline approach has the systematic bias removed; this statistically renders a process with an unbiased mean and an i.i.d. SDFE that is centered on zero. While this approach is not possible for Intel's business, it does reflect the theoretically minimum expected safety stock due to demand variability for a given service level. The second approach leaves the mean forecast biased but employs the modified SDFE calculation in Equation (6) to populate (2); this reflects the approach defined in the *Addressing Forecast Bias* Section. The third approach ignores the forecast bias and uses the SDFE from Equation (3) to populate (2); this was the way Intel initially populated the MEIO tool, as defined in the *Demand Characterization* and *Validating MEIO Results* (*Without Forecast Bias Compensation*) sections.

Figures 7(a) and 7(b) show the ratio of expected inventory levels for the two approaches that do not address the mean forecast bias versus the approach that statistically removes the bias. Any point where the ratio does not equal one can be considered an inefficient point because at this point the approach

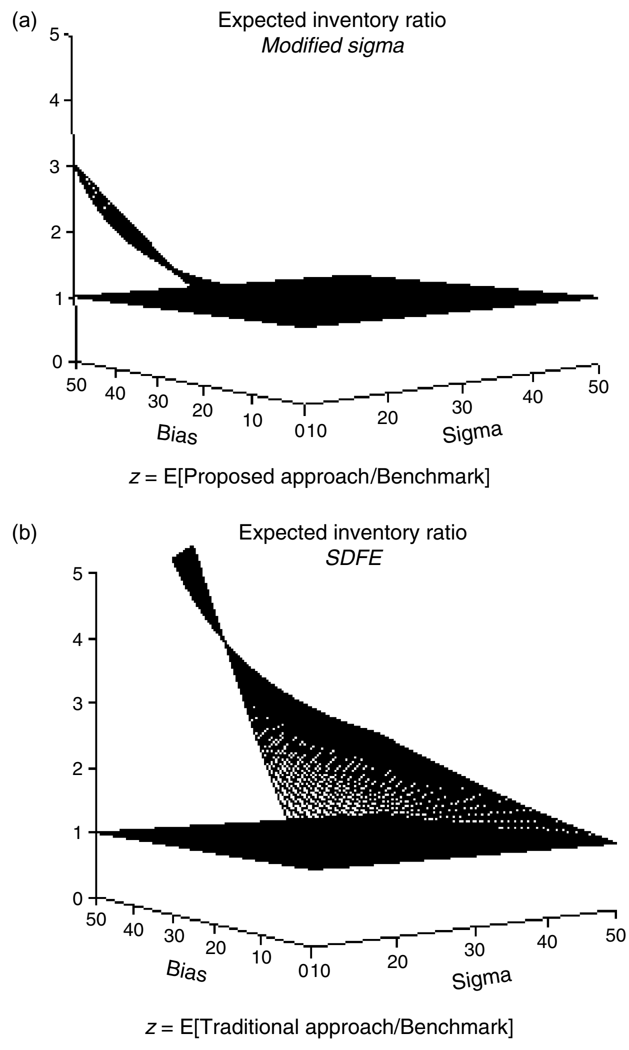

Figure 7: Adjusting the SDFE mitigates bias and delivers optimal expected inventory levels except when the average bias exceeds $F^{-1}(\alpha)\sigma\sqrt{\tau}$. This delivers superior inventory levels over ignoring the bias and not adjusting sigma.

presented in the *Improving Intel's Approach* section produces higher inventory levels versus removing the bias from the raw forecast data.

Figure 7(a) represents the expected inventory ratio for the approach that uses the modified SDFE calculation in Equation (6). As we can see from the mesh plot, even when we do not consider the average bias, the modified SDFE calculation produces the minimum inventory level in most cases. In fact, the modified SDFE approach will produce the same expected inventory level as the theoretically minimum levels as long as the forecast bias over the net replenishment time is less than or equal to $F^{-1}(\alpha)\sigma\sqrt{\tau}$. Only in the case where the bias exceeds $F^{-1}(\alpha)\sigma\sqrt{\tau}$ does the modified SDFE approach generate a nonoptimal expected inventory level that has a percent inefficiency of $Bias/(F^{-1}(\alpha)\sigma\sqrt{\tau}) - 1$; because zero represents the lowest possible value for the modified SDFE, the gap introduced by bias cannot be fully closed once the forecast bias exceeds $F^{-1}(\alpha)\sigma\sqrt{\tau}$. Comparing Figures 7(a) and 7(b) reveals the improvement to expected inventory that the modified SDFE calculation from Equation (6) provides versus using the SDFE calculation in Equation (3).

Figure 8 shows that even when the bias over the net replenishment time exceeds $F^{-1}(\alpha)\sigma\sqrt{\tau}$, the slope of expected inventory as a function of bias is more gradual using the modified sigma method.

In a situation where a biased forecast cannot be corrected, modifying the SDFE can still deliver theoretically minimum expected inventory levels; in a case in which the bias is truly extreme, the resulting expected inventory is far less than not having

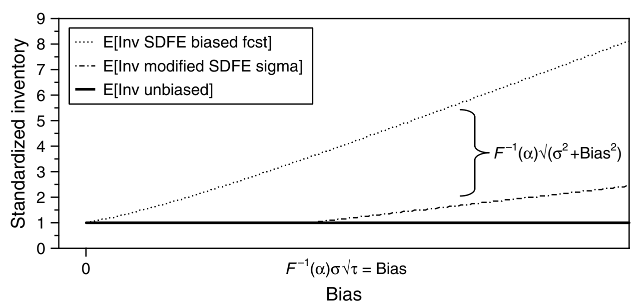

Figure 8: Even with a biased forecast, the modified sigma technique can produce optimal inventory levels as long as the average bias is $\leq F^{-1}(\alpha)\sigma\sqrt{\tau}$.

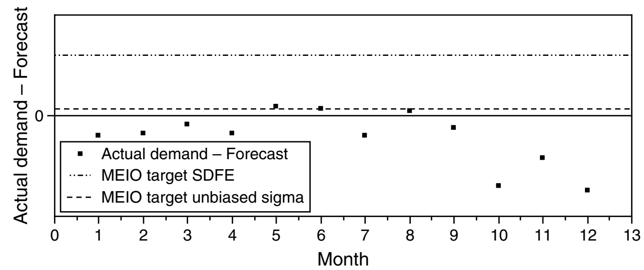

Figure 9: This graph depicts a historical snapshot of an SKU's forecast accuracy residuals and suggested MEIO safety stock based on a calculation of SDFE that considers bias.

modified SDFE. In Intel's case, for a service level that exceeds 80 percent, the modified SDFE method generated the optimal expected inventory levels for 39 out of the 44 SKUs that we analyzed in this paper. In five cases, the forecast bias impact was greater than $F^{-1}(\alpha)\sigma\sqrt{\tau}$.

MEIO Targets Based on Modified SDFE

With the SDFE modified to properly reflect the bias that exists in the raw sales forecast data, we could run the MEIO model again. Figures 9 and 10 demonstrate that these revised MEIO targets are valid when compared with both historical forecasting patterns and planners' knowledge and expectations.

In late 2005, Intel applied SKU-level inventory targets based on MEIO models using the modified SDFE method. Overall, inventory targets were lowered and inventory was redistributed among the SKUs and the stages. As Figure 11(a) displays, on some SKUs, the SKU-level allocation of inventory at the CW stages changed to increase up to seven times the amount under the WOI policy; other SKUs were

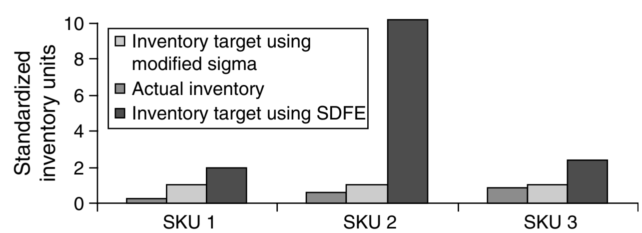

Figure 10: For the SKUs referenced in Figure 4, MEIO targets using the modified SDFE appropriately generated targets that were less than the current inventory levels but also covered the SKUs' historical underforecast pattern.

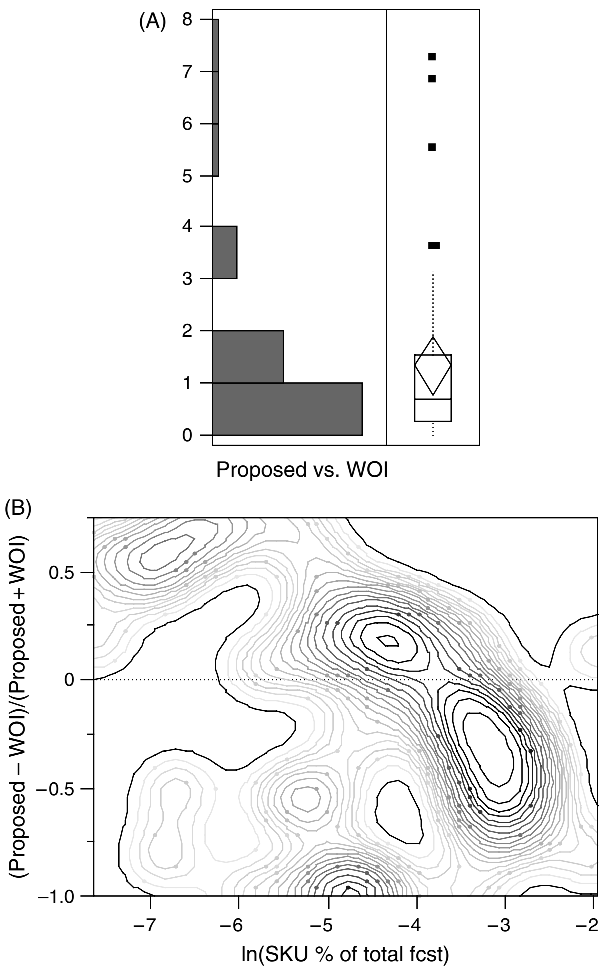

Figure 11: For CW stages, inventory targets that adjusted for forecast bias were lower overall than the management-based WOI policy; however, individual SKU targets ranged from ∼0% to >700% of the original uniform WOI targets.

required to hold almost no inventory. Figure 11(b) demonstrates that reallocation of inventory tended to follow a pattern of increasing inventory on SKUs with lower relative forecasts, while SKUs accounting for a higher percent of the product-family forecast required less than the management-specified WOI policy.

The resulting MEIO inventory targets for the two product families at 95 percent customer-service levels were 17 percent lower in aggregate than the management-specified WOI policy and 71 percent lower than the targets generated by using the unadjusted SDFE estimate from Equation (3).

Project Lessons

Several aspects of this forecasting approach led to quick acceptance by Intel's planning management. First, an easily understood rule of thumb emerged for validating safety-stock targets. For service levels of 95 percent and above, the rule of thumb was that safety stock held to cover forecast error should roughly equal the worst underforecast in an SKU's history. This result made it easy for management to interpret and understand inventory target setting.

In addition to making intuitive sense, the result also makes it easy to tie inventory costs directly to the accuracy of forecasting. This enabled project teams to more accurately estimate the return on investment (ROI) of various efforts to improve the forecasting and planning processes. However, a certain paradox exists with an SKU that is systematically overforecasted: as the average bias is eliminated (i.e., the average forecast error converges to zero, independent of the variability), on average, the likelihood and severity of underforecasting increases; therefore, the safety-stock target increases. This stems from how the modified sigma approach effectively reallocates inventory in the base-stock inventory equation in (1):

$$\tau\mu + F^{-1}(\alpha)\sigma\sqrt{\tau} \longrightarrow (\tau\mu + \mathit{Biasimpact}) + (F^{-1}(\alpha)\sigma\sqrt{\tau} - \mathit{Biasimpact}).$$

Because safety stock target setting occurs with only $F^{-1}(\alpha)\sigma\sqrt{\tau} - \mathit{Biasimpact}$ in mind, a decrease in bias impact increases the safety-stock target. A naive interpretation would lead an inventory analyst to believe that initiatives to improve average forecast accuracy would have negative ROI as safety-stock targets increase. For an analyst, this can be doubly confusing because the inventory on hand will already be higher than the target set through the modified SDFE; to see an indication that a higher safety-stock target is necessary would seem contradictory. However, this will naturally be the result of the whole supply chain equilibrating through elimination of the bias:

$$(\tau\mu + \mathit{Biasimpact}) + (F^{-1}(\alpha)\sigma\sqrt{\tau} - \mathit{Biasimpact}) \xrightarrow{\mathit{Bias}\to 0} \tau\mu + F^{-1}(\alpha)\sigma\sqrt{\tau}.$$

Second, management liked the fact that the planning organization could correctly treat forecast bias without touching the raw sales forecast. In addition to not changing significant organization roles and responsibilities, the raw forecast continued to drive the MEIO model's work-in-process pipeline inventory rather than a demand-data stream that needed statistical correction.

Third, the revised estimation of the SDFE, in addition to being unbiased, is also adaptable because it is independent of how an SKU is forecasted—whether with bias or without, continuous or not, and whether the bias is positive or negative. If forecasting behavior changes, to become either more or less accurate, the modified estimate for the SDFE will adjust accordingly, albeit with some lag.

Finally, inventory targets are measured in constant units of product, rather than as a function of the already-biased demand, such as WOI. This allows inventory planners to plan toward a stationary inventory target, at least until forecast accuracy changes significantly.

However, this adjustment technique is not a panacea. We found the following management-of-change and technical issues with this approach.

As long as there is bias in the forecast, the modified SDFE approach will generate a safety-stock target that should be unobtainable in that the bias will raise or lower the expected inventory to the theoretically optimal level. When a positive forecast bias exists, the safety-stock target is lowered, although with the excess that the forecast bias causes, the expected safety-stock level will be maintained at the optimal $F^{-1}(\alpha)\sigma\sqrt{\tau}$. Likewise, for a forecast with an underforecast bias, the expected safety stock will always fall short of the modified SDFE target.

In addition, a few technical challenges exist in implementing this approach. For example, it is necessary to determine how many past observations are significant enough to rely only on an SKU's own relative forecast accuracy data versus using all the past observations from its product family. Because all SKUs within a family do not demonstrate identical forecast accuracy, it is less desirable to use a broad family distribution. However, that approach may be more effective than using an SKU's relative forecast accuracy data if only a handful of observations exist. The implication of these types of technical issues is that planners must be trained and equipped with a proper foundation in statistical techniques before the planning organization can deploy the method widely.

Finally, planners still have difficulty setting inventory targets to zero on a high-volume product that has always been overforecasted. Despite the presence of overwhelming data, management's nature will still require a leap of faith to cut the safety-stock target to zero. We have seen this approach work in Intel's embedded devices group; however, implementation in each new division will require strong management support.

Appendix A

Below we show a step-by-step process to apply the calculation of the modified estimate of the SDFE in the *Addressing Forecast Bias* section. The data is a one-year sampling from one of the 44 SKUs that Figure 3 depicts. Demand was forecasted at the monthly level; the net replenishment time was also one month. In this example, assume that the next forecast calls for 1,000 units in the following month.

Table A.1 illustrates the raw data and the relative forecast accuracy metric that we presented in Equation (4).

The first step is to sort the months in ascending order of their forecast errors (Table A.2).

In the second step, we take the service level (assumed to be 75 percent in this case), and determine the month with the percentile of underforecasts that matches the service level. In this case, the 10th point

Month	Forecast	Actual demand	Forecast/(Forecast + Actuals) = θ
1	1,000	681	0.59
2	1,000	713	0.58
3	1,000	857	0.54
4	1,000	718	0.58
5	500	609	0.45
6	700	777	0.47
7	800	485	0.62
8	500	550	0.48
9	1,200	992	0.55
10	1,500	438	0.77
11	2,000	1,349	0.60
12	1,539	406	0.79

Table A.1: This table presents forecast and demand data plus the forecast accuracy metric as Equation (4) shows.

Month	Forecast	Actual demand	Forecast/(Forecast + Actuals) = θ
5	500	609	0.45
6	700	777	0.47
8	500	550	0.48
3	1,000	857	0.54
9	1,200	992	0.55
4	1,000	718	0.58
2	1,000	713	0.58
1	1,000	681	0.59
11	2,000	1,349	0.60
7	800	485	0.62
10	1,500	438	0.77
12	1,539	406	0.79

Table A.2: This table shows the result of sorting the raw monthly data in ascending order of forecast error.

out of 12 occurred in month eight, and has a relative forecast accuracy of ~0.48.

Using Equation (6), the estimate of the SDFE is

$$\hat{\sigma}^{Modified} = \left(\frac{(1-0.476)/0.476-1}{0.7}\right)1{,}000 \approx 145.$$

The original SDFE, Equation (3), produces $\hat{\sigma}^{\mathrm{SDFE}} = 546$, an estimate almost four times that produced by the modified SDFE.

Appendix B

Relative Volume Problem

Although we used the modified SDFE based on a standardized forecast accuracy measurement, there were still situations in which inventory targets were unrealistically high. This occurred because, on average, forecasts were biased to be high; however, the larger the SKU's historical forecast, the more likely it was to be overforecasted; and the smaller the SKU's historical forecast, the more likely it was to be underforecasted (Figure B.1). This meant that if a product was approaching the high-volume stage of its life cycle, the SDFE was overstated because the likelihood and size of overforecasting was dependent on both the SKU itself and on its stage in the life cycle.

To correct for this, we modified Equation (6) to consider just the magnitude of past underforecasts, not the relative size as is the case when we use the distribution of θs in Equation (6). Equation (B1) illustrates this:

$$\hat{\sigma}^{Modified} = \max\left\{\frac{(D_i - F_i)_\beta}{t_{\beta,\,df}}, 0\right\}. \tag{B1}$$

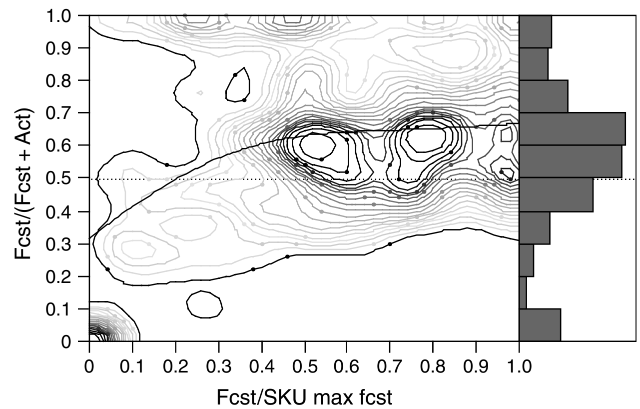

Figure B.1: This graph displays forecast accuracy density and spline fit. As a product's forecast approaches its maximum, the likelihood of overforecasting increases.

The relationship between forecast magnitude and the heterogeneity of forecast error is a continuing topic of research at Intel.

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David Ploudre, CIG Supply Network Planning Manager, writes: "I am the Communications Infrastructure Group (CIG) Supply Network Planning Manager at Intel Corporation, 5000 W. Chandler Blvd., Chandler, AZ 85226. As is referenced below, the 'Embedded Intel Architecture Division' (EIA) Planning department reports directly to me.

"I write this to verify that the authors did conduct the work reported in 'Setting Safety-Stock Targets at Intel in the Presence of Forecast Bias.' Given the breadth and depth of Intel's product portfolio, addressing the matter of forecast bias is critical in order to implement tools that can be deployed across the organization.

"Prior to this work, we had a standardized approach for setting inventory targets at the product-family level that was based on management objectives. Our planning process did not consider the impact that SKU-level forecast bias and variability was having on our ability to set accurate inventory targets and reach/maintain those goals. The correction for bias outlined in this paper allowed us to use scientifically derived inventory targets that directly accommodated the data that exist in Intel's planning systems. The approach outlined in this paper allowed us for the first time to address the impact of forecast bias in a scientific, quantitative, and practical manner.

"The 'Embedded Intel Architecture Division' was the first product group at Intel to develop and use these techniques to adjust inventory targets in the presence of forecast bias. Since then, this idea continues to be developed and integrated into our Planning system and product portfolio and is becoming a standard and highly desired practice in our business model."