INTRODUCTION

A great deal is written about forecasting methods, but very little about how to deal with forecast error in the practical sense of how much safety stock is needed to allow for forecast error when placing manufacturing or purchase orders.

This article describes a process that may help readers to make a start on reducing errors by recognising that they are inevitable, but can be managed by comparing alternative approaches, then selecting one that appears likely to give an acceptable error level.

There are several reasons why forecasts are used to plan inventory levels. They include:

- Developing production requests to manufacturing operations
- Planning for new product launches
- Planning for promotional activity
- Planning for seasonal variations in demand.

There are many situations where forecasting is not required. Where demand is relatively stable, apart from the normal variability that will always exist, the conventional replenishment models – Continuous Review, and Periodic Review in their various forms – provide a sound basis for inventory management. Therefore, don’t use a forecasting process unless you have to.

Even with replenishment systems, frequent review of the parameters is required to ensure that re-order points or ‘order-up-to’ levels reflect current levels of:

- Demand
- Demand variability, measured by the Mean Absolute Deviation *(MAD) or the Standard Deviation
- Lead time
- Lead time variability
- Required service level.

In effect, this is a forecasting system based on the assumption that demand patterns will not change significantly in the short term.

These replenishment models, however, will not suffice where there are strong seasonal demand variations which cannot be met without giving notice to in-company manufacturing operations or external suppliers.

Where forecasting is required, then some element of safety stock will be required to cover for forecast error, and possible lead time variability during the replenishment cycle. One of the key parameters in setting the safety stock level will be the level of forecast error.

Therefore, the simple message is ‘Improving the accuracy of forecasts reduces safety stock requirements in a forecast-based system’. It isn’t the only one – reducing supply lead time, lead time variation and the required service level will also reduce safety stock requirements, as they do with the continuous and periodic review replenishment systems.

FORECASTING METHODS

There are many forecasting systems in use, especially in the Fast Moving Consumer Goods (FMCG) sector. The number of product lines in a large retail organisation ranges from 35,000 to 100,000. If these are to be managed consistently, some computer-based system will be required to analyse demand patterns, and to allow intervention for promotional activity, product introduction, and product renewal.

Methods of forecasting include:

- Moving averages
- Exponential smoothing
- Time series analysis
- Mathematical curve fitting.

The first three of these require the use of seasonal adjustment factors if the forecasts are to achieve reasonable levels of accuracy.

MEASURING FORECASTABILITY

Assuming that you have a large range of Stock Keeping Units (SKUs) to manage, how do you identify those which will work well using a forecasting process, and those which won’t.

One simple measure is to measure the Coefficient of Variation.

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Where the factor is large, it is probable that a statistical forecasting system will not give a good level of accuracy. Figure 1 illustrates four patterns of demand.

What can this analysis tell us about probable levels of forecast accuracy?

- **Product A** – The Coefficient of Variation is very low. This product will give a high level of accuracy using exponential smoothing, or some other technique.

- **Product B** – The Coefficient of Variation is high. Here there are two streams of demand. An underlying and regular demand between 25 and 80 units, overlaid with occasional large demands, probably from a single customer who places orders intermittently. This type of demand will produce inaccurate forecasts, unless the demand planner intervenes to get early warning of impending large orders.

- **Product C** – Here the Coefficient is greater than the mean. This is a pattern of demand which is best managed using the Poisson Distribution. Replenishment is based on ‘use one, order one. Forecasts based on exponential smoothing would set unrealistically high stock levels. In this instance the mean is close to the variance – (the standard deviation squared) – which is the definition of a Poisson demand item. ie. 0.66 squared = 0.44, close to the average demand of 0.4

- **Product D** – Again the Coefficient of Variation is high, indicating that a forecasting process would give high levels of forecast error. This pattern would be typical of a highly seasonal product, or a product where there is only one customer, as found in the ‘Own Label’ grocery products industry. Where the volume of such a product is high, it is necessary, and worthwhile for the demand planner/inventory controller to get close to the customer, probably with the assistance of the Account Manager.

What conclusion can be drawn from these examples?

- You need to identify the products where a forecasting system is likely to work well – and the Coefficient of Variation can give a good indication of this.

- Look at the pattern of demand for each SKU – analysing the demand patterns on a spreadsheet, and calculating the Coefficient of Variation, then sorting the table will show which items will need special attention.

- Be prepared to use other methods of inventory management, rather than rely on forecasts for all items.

- Recognise that an experienced inventory planner will be needed to manage the process.

- If you have products which are likely to work well with a forecasting system. Don’t spend hours agonising over trying to get marginal improvements in forecast accuracy for those items. Time will be better spent getting stock levels right on the unforecastable items which need the knowledgeable intervention of the demand planner.

**MEASURING FORECAST ACCURACY**

Where you have decided that a forecast really is required, you have to choose a forecasting method. However hard you try, you know that forecasts will be inaccurate. Therefore, the exercise is about minimising forecast error.

A measure commonly used is the Mean Absolute Deviation (MAD). This compares actual demand in a period with the forecast made for that period. The difference, whether plus or minus, is treated as an absolute value.

This process would be carried out for the most recent sales history, perhaps over the last 13 – 15 periods. These absolute difference would be averaged to produce the MAD.

This can then be used as the basis for setting a measure of forecast variability. To generate the ‘Standard Deviation of Forecast Error’ the MAD would be multiplied by 1.25. Figure 2 shows the process.

In a forecasting system, this parameter could be reviewed each period. It will be used in setting the safety stock level for the product.

Figure 2 also shows another common measure of forecast accuracy – the Mean Absolute Percentage Error. The lower this figure, the better the forecasting process is working.

**TESTING A FORECASTING METHOD**

Assuming that you have some historical data, and you have a forecasting method in mind, how do you determine how well it is likely to perform? If you are thinking of installing a forecasting system, this is an important issue.

If you want to test a forecasting method you have to:

- Take a sample of historical data. You are going to use the model to see how well it would have performed. Therefore you need, say, 25 periods of demand. 20 of these could be used to build a forecast history, which can then be tested against the remaining known 5 demands. In the model below, based on the Holt-Winters algorithm, there are 25 periods of known demand. This is a model that is based on the exponential smoothing concept. In each period, the underlying demand (level) and trend are recomputed and forecasts are based on these updated values. Different smoothing constants are typically used for the level and the trend.
Decide which is the critical period ahead against which forecast accuracy is to be tested – typically reflecting supply lead time. Two weeks ahead is used in the example below.

Figure 3 shows the accuracy achieved for the ‘two-week-ahead’ forecast for periods 21 – 25, where the forecasts are tested against the known demands.

The MAD of the errors is shown for the periods 21 – 25. It is a small percentage of the average demand in those periods. This suggests that this would be a reasonable forecasting method for this product.

This process should be repeated with some variations in the parameters – smoothing constants for Level and Trend in this case – to see whether forecast accuracy improves.

When a model has been tested, you reach the point where you have to do some real forecasting, based on what has been shown to be a reasonably accurate forecasting method.

It is at this point that you have to determine the safety stock level for the product.

SEASONAL DEMANDS

Where it is self-evident that a product demand is strongly seasonal, the historical demand data must be de-seasonalised before being put through the forecasting model.

Seasonal weightings – weekly or monthly – are typically calculated for product families. The process can be briefly described as follows:

- Divide each historical demand by the appropriate seasonal weighting for the week or month number to which it relates.
- Carry out the forecasting process on the de-seasonalised demand data.
- Produce the forecasts for one or more periods ahead.
- Re-seasonalise the forecast by multiplying the de-seasonalised calculated forecast by the appropriate seasonal weighting factor.
CALCULATING THE SAFETY STOCK IN A FORECAST-BASED SYSTEM

This requires the calculation of the ‘Standard Deviation of Forecast Error’. This is calculated based on the following information:

- The average forecast demand per period – based on recent demand history. \( D \)
- The standard deviation of forecast error – typically derived from the MAD. \( S_1 \)
- The mean supply lead time – time from placing the order based on the forecast, to having the stock available for picking. \( L \)
- The standard deviation of the supply lead time – based on an analysis of historical lead times. \( S_2 \)

This data is put into the formula:

\[
[(L \times S_1^2) + (D^2 \times S_2^2)]^{1/2}
\]

Assume the following values:

- \( L = 3 \) periods
- \( S_1 = 35.4 \) (MAD from Figure 3 x 1.25)
- \( D = 855 \) (From Figure 3)
- \( S_2 = 0.5 \) periods – based on historical analysis.

This gives the result:

\[
[(3 \times 35.4^2) + (855^2 \times 0.5^2)]^{1/2} = 432
\]

Since this calculation covers forecast error and lead time in one figure, the only remaining calculation is to decide on the service level as measured by the number of standard deviations.

The higher the service level, the more standard deviations will be used. For a service level of 99% - 2.33 standard deviations – the safety stock will be:

\[
432 \times 2.33 = 1007
\]

Using the average demand shown above – 855, this represents

\[
(1007 / 855) = 1.18
\]

weeks of average demand.

Figure 4 shows the effect on safety stock requirements of reducing lead time – Case B, lead time variability – Case C, and forecast error - Case D. Case A is the base case set out in Figure 3.

The major reduction in the standard deviation of forecast error can be seen in cases C and D, where the lead time variability is drastically reduced.

CONCLUSION

If safety stocks for items where forecasting is used are to be reduced then one, or more, of the following must be achieved

- Improved forecast accuracy
- Reduced lead time
- Reduced lead time variability
- Reduced service level.

The above process can be tested on a small number of products using a spreadsheet, as done here. Going beyond, say, a couple of hundred SKUs takes you into a requirement for specific application software if you want to make forecasting a regular activity applied to key products.

The purpose of this note is to suggest how you can undertake small scale tests of forecasting methods. Any system that you install should be able to do better than these simple models, but these would give you some sort of benchmark against which to test a ‘real’ forecasting system, bearing in mind that some of your products may be unforecastable using a package.

About the author

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He runs a modelling course for the Institute that shows how to use the functionality of spreadsheets in ways that can make significant improvements in manufacturing planning. He has written a number of short articles for Control.

Jeremy Mant will be delivering a course for the Institute entitled

MODELLING AND INVENTORY CONTROL USING SPREADSHEETS

on 27th/28th June 2002.

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