Forecasting

Including an Introduction to Forecasting using the SAP R/3 System

by

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Introduction and Overview

A key part of supply chain planning involves demand planning and the associated demand forecasting process. The focus here is on the various issues involved in forecasting and their use in the SAP R/3 system.

The objectives of this document are to

- highlight the need for forecasting to manage the supply chain,
- provide statistical time series models for short-term forecasting,
- review forecasting performance metrics and tracking procedures, and
- illustrate how forecasting is done in the SAP R/3 system.

To help develop an understanding of the statistical methods, some example problems are included. It should be noted that this module does not cover regression methods as this topic is covered in depth in many other places.

Forecasting and Supply Chain Planning

Supply chain planning, to a large degree, starts with forecasting. Matching supply and demand is an important goal for most firms and is at the heart of operational planning. It is also of significant importance as the overly optimistic Cisco found in 2001 when it took a $2.2 Billion inventory write-down because of their ability to "forecast demand with near-scientific precision" [1]. Since most production systems can't respond to consumer demand instantaneously, some estimate, or *forecast,* of future demand is required so that the efficient and effective operational plans can be made.

Plant, process, and labor capacity are all set based on the forecasts of future demand. Capacity planning and facility decisions would be based primarily on longer term, aggregate forecasts. However, forecasts are also needed to plan proper inventory levels, which in general, tend to require shorter-term forecasts at a disaggregated level since specific components, parts, and end-items must be stocked for immediate consumer demand.

Forecasts affect most functional areas of the firm and are the starting point for resource allocation decisions. For example, manufacturing must plan production on a day to day basis to meet customer orders, while purchasing needs to know how to align supplier deliveries with the production schedules. Finance needs to understand the forecasts so that the proper levels of investment can be made in plant, equipment, and inventory and so that budgets can be constructed to better manage the business. The marketing function needs to know how to allocate resources for various product groups and marketing campaigns. Forecasts also determine the labor requirements required by the firm so that the human resources function can make proper hiring and training decisions when demand is expected to grow.

[1] "Cisco's Comeback", Business Week Online, November 24, 2003

Forecasting Practice

Forecasts are always wrong, but some are “more wrong” than others. Forecasting the demand for innovative products, fashion goods, and the like is generally more difficult than forecasting demand for more “commodity-like” products that are sold on a daily basis. Aggregate forecasts of a group of similar products are generally more accurate than individual forecasts of the individual products that make up the group. Finally, the longer the forecast into the future, the less reliable the forecast will be.

Forecasting practice is based on a mix of qualitative and quantitative methods. When planning occurs for innovative products, little demand data are available for the product of interest and the degree to which like product demand data are similar is unknown. Thus a large amount of judgment is needed by experts who can use their industry expertise to predict demand. These experts, though, will undoubtedly use historical demand data, even if not directly, in their judgment.

Commodity-like products that are sold everyday, on the other hand, are much more suitable for quantitative models and need very little judgment to forecast demand. Still, when knowledge of certain events leads one to believe that future demand might not track historical trends, some judgment may be warranted to make adjustments in the models which use past data. In this case, a heavy reliance on past data with adjustments based on expert judgment should be the method used for forecasting.

Forecasting should be done primarily for end-item demand. In manufacturing situations, this means there is no real need for forecasting component parts which make up the final item. When production quantities for the end item have been determined, component demand can be computed based on the production plan of the end item and knowledge of the bill of materials (BOM).

Aggregating forecasts across multiple items reduces forecasting errors. A clothing store, for instance, might be able to estimate within a pretty narrow range what the demand will be for men’s dress shirts. But when that store tries to estimate the demand for individual styles, colors, and sizes of shirts, the accuracy of their forecasts will be considerably worse. Firms handle this kind of forecasting problem usually in one of three ways; they either forecast from the bottom up, from the top down, or they start in the middle and work both up and down. The “top down” forecast essentially estimates total sales demand and then divides those sales dollars level by level until the stock keeping unit (SKU) is reached. The “bottom up” method, as one might expect, starts with forecasts at the SKU level and then aggregates those demand estimates level by level to reach a company–level forecast. Another method, one might call the “in-between” method, starts forecasts at the category level (like men’s dress shirts), and then works up to determine store sales and works down to divide up the forecast into styles, colors and SKUs.

The use of management time to make forecasts is relatively expensive when compared to the cost of using statistical forecasting models, and the difference between the costs of these two methods has been increasing in recent years due to the automated acquisition of data from point of sale systems and computer power in general. There can be no substitute for human input in the forecasting process; however, human input can be expensive. In addition, research indicates that for some everyday commodity-type items, simple statistical models work well and in fact work better when not massaged by managers. Still, some managers believe that spending time to make forecasts perfect will solve most of their supply chain problems. There are times when managerial input is needed, but there comes a point where it is better to understand the inaccuracy in the forecast and plan accordingly. Once a good forecasting process (procedures, techniques, models and management oversight) has been put in place, continual refinement has little value and can even hurt the forecasting process.

Supply Chain Improvements for Better Forecasts

Since forecasts are never accurate, two common solutions are often proposed to “fix” forecast errors. The first is to reduce the lead time to react sooner to changes. This is a good partial solution, but reducing lead times is not always easy to do and is often expensive. In addition, shortening the lead time, in many cases, just moves the problems from one part of the supply chain to another. The second is to “make to order” so that inventory doesn’t need to be produced in advance of demand. This solution is also good, but like shortening the lead time, tends to shift demand to the next level of the supply chain. Furthermore, producing to order still requires forecasts, to be able to keep the right quantities of raw material on hand. So while these ideas help improve certain aspects of the forecasting problem, they do not eliminate the need for some kind of forecasting methods.

A more recent proposal to fix forecast errors is to use *collaboration*. The idea is that if different parts of the supply chain collaborate on a common forecast and everyone plans based on that single forecast; then there is little need for one part of the chain to hedge based on the uncertainty of what is done in other parts of the chain. Intra-firm collaboration, you would think, would be common place – seems that a little common sense would dictate that everyone in a firm come together with a common set of forecast figures. But this is rarely the case. Marketing has a set of forecasts, so too does operations. Sales has their forecast and it’s possible that for budgeting purposes Finance uses still another. The advancement of enterprise resource planning (ERP) systems is helping ensure that there is only one forecast, based upon the principles of a single data repository used by all areas of the enterprise.

Once functional areas within a firm agree on a common forecast, the next step is for inter-firm agreement. This type of collaboration is tougher, but many believe it is an essential step in the continual improvement of the supply chain. The collaborative planning, forecasting, and replenishment (CPFR) multi-industry initiative is aimed at providing this kind of integrative forecast between so-called “trading partners” – different levels in the supply chain. Supply chain advanced planning system (APS) models and software packages are designed to connect the various supply chain players so that this collaboration can be completed successfully. But there is much to do in this area to end the second guessing that is so prevalent today.

Forecasting Methods

Forecasting is based on a mix of qualitative and quantitative inputs. The type of product and that product's impact on supply chain costs determine how much human input is used and how sophisticated the forecasting model should be.

Qualitative Input

Human judgment can be captured in a number of ways. Three common approaches include an Individual Market Expert, Group Consensus, and the Delphi Method. All of these are sometimes referred to as Expert Opinion methodologies since they require people with some knowledge of the products and markets developing forecast estimates for planning needs.

Individual Market Experts can be hired to watch for industry trends, perhaps even by geographic area, and might even work with sales people to estimate future demand for products. Individuals, though, have biases that they may not be aware of and there is a limit to how much information one person can obtain. To overcome this, even though it can be considerably more expensive, is to use groups of experts.

Group Consensus involves bringing together a team of experts, hopefully from different functional areas, to reach consensus on future forecasts for a product or a group of products. Group Consensus forecasts tend to bring together different factions of the company so that everyone tends to "buy-in" the final numbers. The group gets to make sure that over-zealous managers don't over-forecast just to try to meet firm expectations for growth. The group also gets to make sure someone doesn't play conservative and under-forecast because that person thinks it is less risky to "low-ball" the forecast. But, building consensus has its pitfalls as well. When people from different ranks in the firm come together, there can be a tendency for low-ranking personnel to at some point acquiesce to the higher-ranking managers in the group. This defeats the point of coming to a consensus agreement and can be a real problem with certain personalities. One way to overcome this issue is to come to an anonymous consensus by using something known as the Delphi Method.

The Delphi Method requires one person to administer and coordinate the process and poll the team members (respondents) through a series of sequential questionnaires. While the team members need to be people who have some expertise in the area of interest to the forecast, the administrator only needs to have some knowledge of how to coordinate the effort without unduly influencing the results. The questionnaires that are sent to the members involve not only estimates of demand, but they are aimed at determining how the member is reaching that estimate. Once everyone has returned the questionnaires, the administrator must summarize the results and send a summary report to all of the members, but, with the identity of who made which forecast hidden from the team. Along with the summary is another questionnaire which in some ways builds off of the previous forecasts and assumptions used in those forecasts. This process of questionnaire, summary, questionnaire, summary continues until the participants reach some consensus on the forecast. Obviously this method can be both time consuming and rather expensive to administer but it can lead to good forecasts and in addition, it establishes over time the important inputs to the process. Three rounds seems to be a good compromise between forecast quality and the cost and effort involved.

Quantitative Input

Quantitative analysis typically involves two approaches: causal models and time-series methods. Causal models establish a quantitative link between some observable or known variable (like advertising expenditures) with the demand for some product. Time series analysis involves looking at historical demand for a product to forecast future demand.

The most common types of *Causal Models* are regression analysis and econometric models. While regression models can be quite involved, simple linear regression is often used, whereby a straight line of the form $Y = mX + b$ is used to describe the relationship between the dependent variable Y and the independent variable X. The line is fit through a set of points such that the squared distance from the line is minimized, thus a "least square" fit. Econometric models are usually some form of multivariate regression model where the independent variables (many Xs) represent factors like disposable income and industrial output from the economy. The mathematical details of regression are not covered here.

There are a number of different kinds of *Time Series Models*, most of which work on the assumption that historical demand can be "smoothed" by averaging and that past demand "patterns" will continue to occur in the future. Simple time series analysis includes models such as the Weighted Moving Average and Basic Exponential Smoothing. More complex time series methods include factors for trends, seasonal patterns, and economic cycles. The remainder of this reading focuses on these time series models.

Simple Time Series Models

Some of the most popular forecasting methods, especially in software packages, are commonly referred to as *time series models*. These models make use of past data to predict future demand. This type of forecasting method is especially relevant for items which are continuously ordered as these methods can be "automated" in computer information systems to a large degree.

The models assume that each observed demand data point is comprised of some systematic component and some random component. The time series model is designed to predict the systematic component but not the random component. The idea is similar to the logic of quality control charts in that you don't try to react to the process variability as long as it is within the control limits. Reacting (or changing the forecast model) because of errors that are random is only likely to increase the error in future forecasts. What is needed is to try to predict the range or variation of this random error. Models can be designed for just about any type of systematic change in demand, but there is real danger in trying to predict the random component.

Projection

The easiest time series method simply projects future demand based on the last period's demand. The forecast for the next period $t+1$, F_{t+1}, is simply a projection of this period t demand, D_t

$$F_{t+1} = D_t \tag{1}$$

This method, although easy to use, doesn't make use of data that is easily available to most managers; thus, using more of the historical data should improve the forecast. Averages of past demand might be more useful and are discussed next.

Simple Moving Average (MA)

The simple moving average forecast makes use of more of the historical demand data than just the last period's demand. An n-period moving average uses the last n periods of demand as a forecast for next periods demand:

$$F_{t+1} = \frac{D_t + D_{t-1} + D_{t-2} + \ldots + D_{t-n+1}}{n} \tag{2}$$

This forecast model is most useful where the demand level is fairly constant over time. The model then makes simple adjustments to this average level rather than assuming that the level is forever constant. Its advantage over the projection model is that by averaging, the forecast won't tend to fluctuate as much.

The average of the previous n periods can be viewed as the estimate of the average "level" of demand as of period t. Thus, one could define the level, L_t, as

$$L_t = \frac{D_t + D_{t-1} + D_{t-2} + ... + D_{t-n+1}}{n} \quad (3)$$

and thus the forecast, F_{t+1}, is just the last estimate of the level of demand.

$$F_{t+1} = L_t \quad (4)$$

This forecast is no different than the direct forecast given above in Equation 2, but the interpretation allows for an easier presentation of the more advanced forecasting models to come.

Weighted Moving Average (WMA)

One shortcoming of the simple moving average is the equal weighting of data. For instance, a 5-period moving average weights each of the past 5 demand observations the same – each has a 20% impact on the forecast. This runs counter to ones intuition that the most recent data is the most relevant. Thus, the weighted moving average allows for more emphasis to be placed on the most recent data. This forecast is:

$$F_{t+1} = L_t = \frac{w_t D_t + w_{t-1} D_{t-1} + w_{t-2} D_{t-2} + ... + w_{t-n+1} D_{t-n+1}}{w_t + w_{t-1} + w_{t-2} + ... + w_{t-n+1}} \quad (5)$$

where w_t is the weight applied to the demand incurred in period t, w_{t-1} is the weight given to that of period t-1, and so on

Intuitively, the expectation would be that the more recent demand data should be weighted more heavily than older data; so, generally, one would expect the weights to follow the relationship $w_t \geq w_{t-1} \geq w_{t-2} \geq \ldots$.

Basic Exponential Smoothing (BES)

Nice properties of a weighted moving average would be one where the weights not only decrease as older and older data are used, but one where the differences between the weights are "smooth". Obviously the desire would be for the weight on the most recent data to be the largest. The weights should then get progressively smaller the more periods one considers into the past. The exponentially decreasing weights of the basic exponential smoothing forecast fit this bill nicely. The forecast equation is given by:

$$F_{t+1} = L_t = \alpha D_t + (1 - \alpha) F_t \quad (6)$$

where α is a smoothing parameter between 0 and 1.

To show that this forecast is in fact a weighted average forecast, it is instructive to look at the algebraic expansion of this model.

Since $F_t = \alpha D_{t-1} + (1 - \alpha) F_{t-1}$

$$F_{t+1} = \alpha D_t + (1-\alpha)[\alpha D_{t-1} + (1-\alpha)F_{t-1}]$$
$$F_{t+1} = \alpha D_t + \alpha(1-\alpha)D_{t-1} + (1-\alpha)^2 F_{t-1}$$

This too can be expanded since $F_{t-1} = \alpha D_{t-2} + (1-\alpha)F_{t-2}$

$$F_{t+1} = \alpha D_t + \alpha(1-\alpha)D_{t-1} + (1-\alpha)^2[\alpha D_{t-2} + (1-\alpha)F_{t-2}]$$
$$F_{t+1} = \alpha D_t + \alpha(1-\alpha)D_{t-1} + \alpha(1-\alpha)^2 D_{t-2} + (1-\alpha)^3 F_{t-2}$$

Continuing this expansion, the model can be written as:

$$F_{t+1} = \alpha D_t + \alpha(1-\alpha)D_{t-1} + \alpha(1-\alpha)^2 D_{t-2} + \alpha(1-\alpha)^3 D_{t-3} + \ldots \quad (7)$$

Thus, the exponential smoothing model is actually a weighted moving average model with special weights. These weights get continuously smaller as they are applied to periods farther away from the current period. With some algebra, it can be shown that these weights sum to one

$$\alpha + \alpha(1-\alpha) + \alpha(1-\alpha)^2 + \alpha(1-\alpha)^3 + \ldots = 1 \quad (8)$$

Even though these weights have nice properties, it is not necessary to keep track of each of the weights. In addition, a system running the model does not need to store the historical data or does it need to compute anything based on old data. The only thing that is needed is the smoothing factor α, last period's demand, and last period's forecast. The nice thing about the model is that all past demand data is effectively "stored" in the last period's forecast.

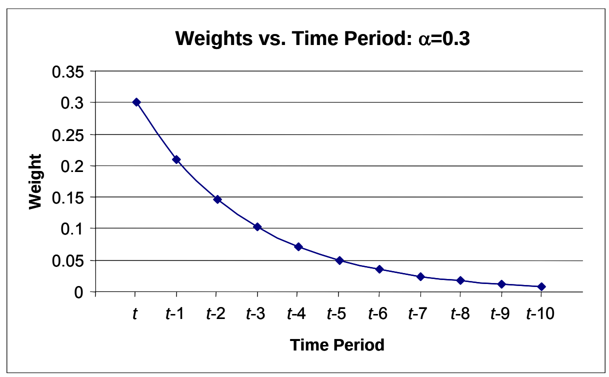

Figure 1: Effective Weights for BES

Simple Time Series Example

The models presented above are now illustrated using a simple data set. Eight periods of demand data for a product are given for January through August in Table 1. The period designation in the table is the same as referred to in the models.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Period	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t
Demand	45	50	42	46	52	47	41	48

Table 1: Seasonal Estimates and Initial Seasonal Factors

The firm wishes to forecast demand for September (period t+1). These calculations are presented below.

Simple Projection

$F_{t+1} = D_t$; $F_{t+1} = 48$.

Simple Moving Average (using 4 periods)

$$F_{t+1} = \frac{D_t + D_{t-1} + D_{t-2} + ... + D_{t-n+1}}{n} = \frac{48 + 41 + 47 + 55}{4} = 47$$

Weighted Moving Average (using 4 periods with w_t =0.4, w_{t-1} =0.3 w_{t-2} = 0.2, w_{t-3} = 0.1)

$$F_{t+1} = \frac{w_t D_t + w_{t-1} D_{t-1} + w_{t-2} D_{t-2} + ... + w_{t-n+1} D_{t-n+1}}{w_t + w_{t-1} + w_{t-2} + ... + w_{t-n+1}}$$
$$= \frac{0.4(48) + 0.3(41) + 0.2(47) + 0.1(55)}{1} = 46.1$$

Basic Exponential Smoothing (with α=0.2)

To employ BES, the firm uses the past demand data to *train* the model. To do this training, forecasts need to be computed for each period for which there is demand data. Table 2 shows the forecast for September of 46.4 and the computations needed to obtain that forecast using the exponential model. By letting the forecasting model run through past data, a sort of smoothing takes place so that future forecasts are based on good weights. This training with past data also allows the forecaster to measure the forecast errors based on the model assuming that it was actually used in the past to make forecasts.

Month	Period	D_t Demand	$0.2(D_t)+0.8(F_t)$	F_t Forecast
Jan	t-7	45		47.0
Feb	t-6	50	0.2(45)+0.8(47.0)	46.6
Mar	t-5	42	0.2(50)+0.8(46.6)	47.3
Apr	t-4	46	0.2(42)+0.8(47.3)	46.2
May	t-3	52	0.2(46)+0.8(46.2)	46.2
Jun	t-2	47	0.2(52)+0.8(46.2)	47.3
Jul	t-1	41	0.2(47)+0.8(47.3)	47.3
Aug	t	48	0.2(41)+0.8(47.3)	46.0
Sep	t-1		0.2(48)+0.8(46.0)	46.4
* Assume that the forecast for January was 47				

Table 2: BES Calculations

Forecast Accuracy

Since forecasts are always wrong, an estimate of the inaccuracy of the forecast can be just as helpful as the forecast of the expected demand. So a good forecast needs to include a mean and an estimate of how the forecast will vary around the mean. This measure helps us understand the risk of the forecast and allows us to make decisions allowing for variability that is present. Forecasting involves estimating more than the expected demand – it involves trying to estimate the uncertainty as well.

To ascertain how well a forecast model is working, actual past demand information is compared to the forecast for that period. These forecast errors, not only tell a firm how well their forecast system is working, they also provide information about how much risk there is in the forecast by helping a manager understand the inherent variation in the demand. An estimate of the future forecast variation is based, at least in part, on the variation of past forecasts. Many times this estimate of the accuracy of a forecast is consistent over time and can be used to establish upper and lower estimates of expected demand.

The *forecast error* for period *t* is defined as[2]

$$E_t = F_t - D_t \tag{9}$$

Several different error metrics are used in practice, with different strengths. They are based on various functional sums of these individual period-t forecast errors as explained below.

Average Error and Bias

The simple *average error* over *n* periods is

$$AE_n = \frac{1}{n}\sum_{i=1}^{n} E_i \tag{10}$$

but one would expect that a good forecast would be such that the expected value of AE_n is zero since positive and negative deviations should cancel each other out. In fact, it would be good to know the value of AE_n, since it indicates how good the forecast is tracking the actual demand. A similar more common measure, known as the *bias*, is usually used to track this "systematic" error and is given as:

$$bias_n = \sum_{i=1}^{n} E_i \tag{11}$$

Managers are interested in forecasts with no bias. When a bias exists, it is likely that the wrong functional forecast model is being used. Systematic bias should, theoretically, be something that can be eliminated by introducing some factor in the model to remove it from the forecast. Thus, this simple error measure can be one of the most important in determining if the correct forecasting model is being used.

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[2] Some authors define error as $E_t = D_t - F_t$. This definition requires the user to be aware of how to interpret the positive or negative sign of the errors.

Mean Absolute Deviation

A common average error measurement used in many companies is known as the mean absolute deviation, or *MAD*. Mathematically, it is represented as

$$MAD_n = \frac{1}{n}\sum_{i=1}^{n}\left|E_i\right| \tag{12}$$

where $|E_i|$ is the absolute value of E_i. By taking the absolute value of the error terms, this error measurement captures the positive and negative deviations between the forecast and the actual demand.

Mean Absolute Percentage Error

A measure which is closely related to the MAD, but which expresses the magnitude of the error relative to the magnitude of the demand is known as the mean absolute percentage error, or *MAPE*. To express this relative measure as a percent, the average ratio is multiplied by 100.

$$MAPE_n = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{E_i}{D_i}\right| \times 100 \tag{13}$$

Mean Squared Error

Another measure of average error is known as the mean squared error, or *MSE*. This terminology should be a familiar to those who have used regression models. Here, instead of simply averaging the deviations of the forecast as compared to the actual demand, the deviations are squared, giving more weight to those errors which are the farthest from the actual demand.

$$MSE_n = \frac{1}{n}\sum_{i=1}^{n}E_t^2 \tag{14}$$

Tracking Signal

To automatically detect when a forecast model is no longer producing good forecasts, a measure known as a *tracking signal* is often used.

$$\text{Tracking Signal} = \frac{bias}{MAD} \tag{15}$$

This tracking signal is a measure that can be used in a control-chart-like manner so that when an out-of-control state is reached, the forecasting model can be revised to get things back in control. By dividing the bias by the MAD, the control limits for this "unit-less" measure are the same for every product being forecast and therefore separate control limits need not be kept for each product. Instead, a common rule of thumb is when the tracking signal reaches a value of positive or negative "6", it is time to investigate the forecasting model.

Forecast Error Example

To illustrate some of these error measures, the demand data and forecasts from the example problem presented in Table 2 will be used. The demand is compared to the forecast for each period with the resulting errors give in Table 3. This provides values for the error, E_i, for each period t from January through August. The last two columns of this table show the forecast error and the squared forecast error for each of the periods of interest.

	D_t	F_t	$E_t = F_t - D_t$	
Month	Demand	Forecast	Error	E_t^2
Jan	45	47.0	2.0	4.0
Feb	50	46.6	-3.4	11.6
Mar	42	47.3	5.3	27.9
Apr	46	46.2	0.2	0.1
May	52	46.2	-5.8	33.9
Jun	47	47.3	0.3	0.1
Jul	41	47.3	6.3	39.4
Aug	48	46.0	-2.0	3.9

Table 3: Seasonal Factors

$$bias_{Jan-Aug} = \sum_{i=Jan}^{Aug} E_i = 2.0 - 3.4 + 5.3 + 0.2 - 5.8 + 0.3 + 6.3 - 2.0 = 2.9$$

$$MAD_{Jan-Aug} = \frac{1}{n}\sum_{i=Jan}^{Aug} |E_i| = \frac{2.0 + 3.4 + 5.3 + 0.2 + 5.8 + 0.3 + 6.3 + 2.0}{8} = \frac{25.3}{8} = 3.2$$

$$MSE_{Jan-Aug} = \frac{1}{n}\sum_{i=Jan}^{Aug} E_t^2 = \frac{2.0^2 + 3.4^2 + 5.3^2 + 0.2^2 + 5.8^2 + 0.3^2 + 6.3^2 + 2.0^2}{8} = \frac{120.8}{8} = 15.1$$

$$\text{Tracking Signal (as of Aug)} = \frac{bias}{MAD} = \frac{2.9}{3.2} = 0.9$$

Smoothed Error Measures

Since errors are sometimes used to estimate demand variation, it is useful to think about an exponentially smoothed MAD so that recent errors are weighted more heavily. Smoothing the error is very similar to the basic exponential forecasting technique. Thus, each period a new MAD is computed as

$$MAD_t = \delta |E_t| + (1-\delta) MAD_{t-1} \tag{16}$$

where δ is a smoothing parameter between 0 and 1.

Errors as an Estimate of Forecast Uncertainty

Forecasts usually consist of just a mean; but, an estimate of the standard deviation of the uncertainty of future forecasts can be just as important. The firm needs to know how much risk is in the forecast. For example, good inventory models need some measure of demand uncertainty, or more accurately, forecast uncertainty, to determine the proper levels of safety stock inventory. Inventory models which use past demand variation are likely calling for too much safety stock; a good forecast may be able to predict some of this uncertainty and the safety stock is only needed for the unpredictable part.

Two common measures of the standard deviation of the forecast errors are presented next. One of these is based on the absolute deviation. When forecast errors are normally distributed and have no bias, the MAD can be used to estimate the standard deviation,

$$\sigma = 1.25 MAD\,. \tag{17}$$

The other measure is based on the direct estimate of mean squared deviation statistic and is given as

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n}(E_t - \overline{E})^2}{n-1}}\,. \tag{18}$$

A "Reaction-to-Error" Interpretation of Exponential Smoothing

Since $F_t = E_t + D_t$, the forecast using the exponential smoothing model can be rewritten as

$$F_{t+1} = \alpha(F_t - E_t) + (1-\alpha)F_t \tag{19}$$

which, with a little algebra, can be rewritten as

$$F_{t+1} = F_t - \alpha E_t \tag{20}$$

Thus, each new forecast can be interpreted as the past forecast adjusted by some percentage of the last forecast's error. When the forecast error is positive, the forecast overestimated the demand; therefore, the next forecast needs to be reduced. The smoothing parameter α determines by how much the forecast should be modified.

Multi-Factor Time Series Methods

Forecasts for demand which include some pattern like trend or seasonality require factors for such patterns. The simple time series models above include only one factor, which for the average *level* of demand. When the underlying demand has for instance a trend, these simple models do not perform well – there can be a significant bias in the forecast. The data presented in numerical and graphical form in Figure 2, for an item known as Bike 3023, has a definite trend component.

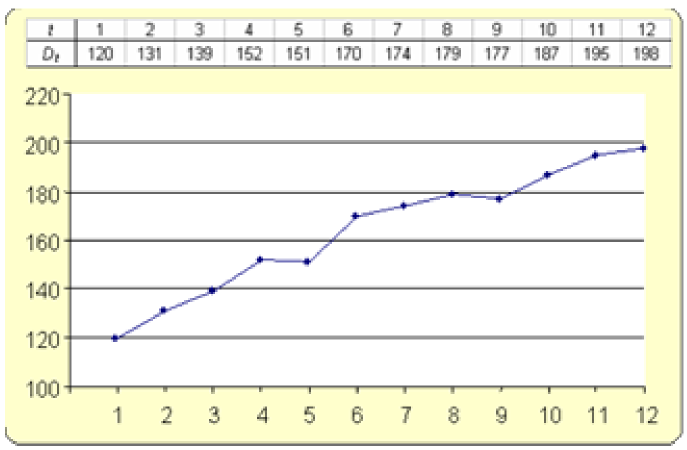

Figure 2: Bike 3023 Demand Data with Trend

If the basic exponential smoothing model with a smoothing factor of α=0.2 is used to forecast, the forecast values, along with the associated errors and bias are as shown in Table 4.

t	D_t	F_t	E_t	$Bias_t$
1	120	122.0	2.0	2.0
2	131	121.6	-9.4	-7.4
3	139	123.5	-15.5	-22.9
4	152	126.6	-25.4	-48.3
5	151	131.7	-19.3	-67.7
6	170	135.5	-34.5	-102.1
7	174	142.4	-31.6	-133.7
8	179	148.7	-30.3	-164.0
9	177	154.8	-22.2	-186.2
10	187	159.2	-27.8	-213.9
11	195	164.8	-30.2	-244.2
12	198	170.8	-27.2	-271.3

Table 4: Example Data with Forecast

Note that one can observe the bias without the calculations since the error is always negative starting in period 2. This shows that the forecast model is always underestimating the demand and is a good indication that the wrong forecast model is being used. One can observe this pattern in Figure 3 where the forecast is shown along with the demand and the forecast is always under forecasting or lagging the demand. Therefore, demand that has some pattern like a trend or seasonality should be forecast with a model that contains the adjustment factor for the pattern.

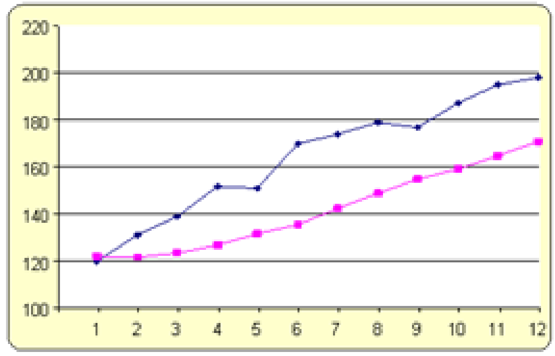

Figure 3: Demand and Forecast Information

Trend-Enhanced Forecasting Models

The functional form of a model which forecasts demand with a trend parameter requires two components, a level component, L, and a trend component, T. When T_t is used to represent an estimate of the trend as of period t, the model for forecasting one period into the future is

$$F_{t+1} = L_t + T_t \tag{21}$$

The additive trend adjustment is one of the most commonly used and is sometimes referred to as Holt's Model. To forecast the 'r^{th}' period into the future, the model is

$$F_{t+r} = L_t + rT_t \tag{22}$$

Exponential Smoothing Updates – Holt's Model

Each period when more information becomes available, the level and trend factors can be updated. This is done with equations very similar to the equations for the basic exponential smoothing model presented earlier. For the basic exponential smoothing model, a smoothing parameter α was used to determine how much of the new demand information should be included in the level factor. Since there are now two factors, level and trend, a second smoothing parameter β is needed for determining the amount of smoothing to be done on the trend factor. Values for β are between 0 and 1. The updating equations for each factor for the case of additive trend (Holt's model) are

$$L_t = \alpha D_t + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{23}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{24}$$

Trend- and Seasonality-Enhanced Forecast Models

When both trend and seasonal factors are present, along with the average level factor, the forecast equation is a combination of the three factors. The most common model and one known as Winters' Model, assumes an additive trend factor and a multiplicative seasonality factor. This model for forecasting one period into the future is

$$F_{t+1} = (L_t + T_t) \times S_{t+1} \tag{25}$$

The factor for seasonality, S_{t+r}, is the seasonal factor for the period $t+r$, r periods in the future. Note that there is a seasonal factor for every "season". If the forecast is quarterly, then there are four seasonal factors. If the forecast is done monthly or weekly, then there are twelve or 52 seasonal factors respectively. In some short-term forecasting situations, where demand varies by the day of the week, there could be a seasonal factor for each day of the week, or seven factors.

For forecasting r periods into the future, the form is

$$F_{t+r} = (L_t + rT_t) \times S_{t+r} \tag{26}$$

Exponential Smoothing Updates – Winters' Model

Just as was done for the additive trend model (Holt's model), the factors for additive trend and multiplicative seasonality (Winters' model) can be updated as new information becomes available. In addition, since there are now three factors, a third smoothing parameter γ is needed for seasonality. The updating equations are then

$$L_t = \alpha \frac{D_t}{S_t} + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{27}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{28}$$

$$S_{t+p} = \gamma \frac{D_t}{L_t} + (1-\gamma)S_t \tag{29}$$

where p is the number of "seasons" (e.g., p=12 for monthly data with a yearly cycle).

Model Initiation and Forecasting

Just as was the case for the basic exponential smoothing model, it is important to find good initial starting factors and then "train" the model. But for the multi-factor models, this is a little more involved. Two sets of example data are used below to illustrate this initiation on Holt's and Winters' models.

Holt's Additive Trend Model Example

Managers at Dynostasio want to set up forecasting models for their most popular products. The demand for one of their products which has seen phenomenal growth since its introduction is shown in Table 5. This product has been on the market since January of 2003 and thus the there is demand data for this product for eleven periods through November of 2003. An analyst for the firm has decided to use Holt's Model to forecast future demand and in particular come up with an estimate of demand for December of 2003.

Period	Time Prd	Demand
1	Jan 2003	1404
2	Feb 2003	1506
3	Mar 2003	1521
4	Apr 2003	1658
5	May 2003	1716
6	Jun 2003	1805
7	Jul 2003	1919
8	Aug 2003	1980
9	Sep 2003	2077
10	Oct 2003	2220
11	Nov 2003	2264
12	Dec 2003	

Table 5: Dynostasio Monthly Demand

Since the model assumes an additive trend, a straight line can be fit to the data to estimate the initial level factor (the intercept) and the initial trend factor (the slope of the line). A linear regression yields the following

Intercept: 1297 Slope: 87.9

These two terms then become the estimates of L and T as of period 0 (demand was regressed against the period numbers 1 through 11) so that

$L_0 = 1297$ $T_0 = 87.9$

Using the forecast equation, the forecast for period 1 becomes

$$F_{t+1} = L_t + T_t \quad \Rightarrow \quad F_1 = L_0 + T_0 = 1297 + 87.9 = 1384.9$$

To continue, the firm now observes the first period of demand, D_1=1404. With this information, the level and trend factors can now be updated so that they are current as of period 1. The analyst has chosen a smoothing parameter of α=0.2 for the level factor.

$$L_t = \alpha D_t + (1-\alpha)(L_{t-1} + T_{t-1})$$
$$L_1 = \alpha D_1 + (1-\alpha)(L_0 + T_0) = 0.2(1404) + (1-0.2)(1297+87.9) = 1388.7$$

Similarly, with a smoothing parameter of β=0.3 for the trend factor

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$
$$T_1 = \beta(L_1 - L_0) + (1-\beta)T_0 = 0.3(1388.7 - 1297) + (1-0.3)87.9 = 89.0$$

A forecast for period 2 can now be made

$$F_{t+1} = L_t + T_t \quad \Rightarrow \quad F_2 = L_1 + T_1 = 1388.7 + 89.0 = 1477.8\,*$$

(* Note that some calculations will be slightly affected by rounding.)

The rest of the calculations are shown in Table 6, including the forecast for period 12, December of 2003. Note that the period 0 numbers are the initial values of the level and trend obtained from the regression.

Period	Time Prd	Demand	Level	Trend	Forecast	Error
0			1297.0	87.9		
1	Jan 2003	1404	1388.7	89.0	1384.9	-19.1
2	Feb 2003	1506	1483.4	90.7	1477.8	-28.2
3	Mar 2003	1521	1563.5	87.6	1574.2	53.2
4	Apr 2003	1658	1652.5	88.0	1651.1	-6.9
5	May 2003	1716	1735.5	86.5	1740.4	24.4
6	Jun 2003	1805	1818.6	85.5	1822.0	17.0
7	Jul 2003	1919	1907.1	86.4	1904.1	-14.9
8	Aug 2003	1980	1990.8	85.6	1993.5	13.5
9	Sep 2003	2077	2076.5	85.6	2076.3	-0.7
10	Oct 2003	2220	2173.7	89.1	2162.1	-57.9
11	Nov 2003	2264	2263.0	89.2	2262.7	-1.3
12	Dec 2003				**2352.1**	

Table 6: Forecasts and Level and Trend Factor Updates

Also in Table 6 are the errors calculated by using the model to forecast the past data. Most importantly, it can be observed that there is not a pattern to these errors. Thus, there is no systematic bias that would indicate the use of a wrong model.

Winters' Additive Trend, Multiplicative Seasonality Model Example

The distribution manager of Jackets-and-Such wants to set up a forecasting model for one of the firm's more popular products. The demand for this product is shown in Table 7.

Period	Time Prd	Demand		Period	Time Prd	Demand
1	Q1 2000	98		9	Q1 2002	127
2	Q2 2000	106		10	Q2 2002	130
3	Q3 2000	109		11	Q3 2002	136
4	Q4 2000	133		12	Q4 2002	159
5	Q1 2001	107		13	Q1 2003	139
6	Q2 2001	116		14	Q2 2003	143
7	Q3 2001	121		15	Q3 2003	153
8	Q4 2001	146		16	Q4 2003	177

A plot of this data indicates a significant seasonality along with growth over the last four years, as can be seen in Figure 4. The manager has decided that the appropriate forecasting model should be one with additive trend and multiplicative seasonality (Winters' Model). Initialization for this model is much like that of the trend only model shown above. The goal is to fit a straight line to the data and then see how far off that line each of the seasons are, thus finding the seasonal factors. One way would be to hand fit a line to the data. Another way would be to use regression, like in Holt's model, but in order to use linear regression; the data must first be deseasonalized.

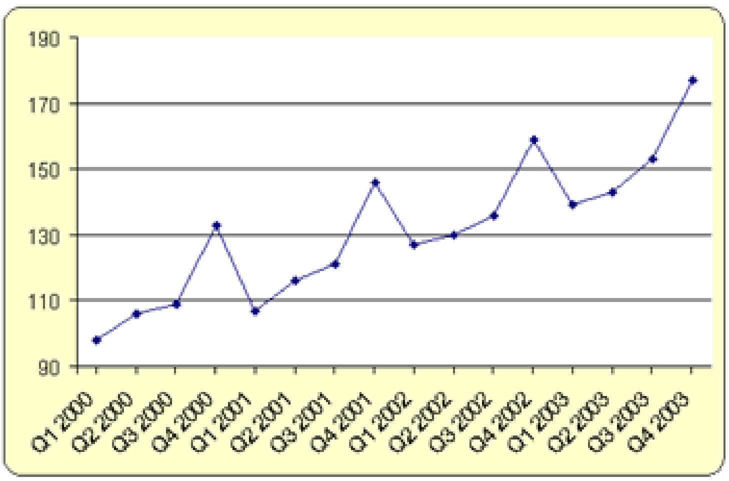

Figure 4: Plot of Demand Showing Trend and Seasonality

Deseasonalizing Demand

Deseasonalizing data essentially requires two steps:

1. Finding the average seasonal demand over a complete set of seasons for all data available.
2. Ensuring that the averages are centering on the appropriate period.

For demand data, seasons can be quarters of the year, months of the year, 4-week periods of a year, weeks of the year, and any other collection of periods where one could possibly observe a recurring pattern. When seasons are taken to be quarters for instance, one can find the average deseasonalized quarterly demand by taking averages over any four consecutive quarters. Using the data from Jackets-and-Such, the average quarterly demand over the first year is

$$\overline{D}_{2.5} = \frac{98+106+109+133}{4} = 111.5$$

Since this is the average over the first four periods, this demand average is centered on period 2.5, which is the subscript on the average demand. This can be seen in Table 8 where the first set of dark diagonal lines show the 111.5 as the average over the demand data from 98 to 133. In similar fashion, the average value of 113.5 is found by taking the average over four consecutive quarters starting with period 2.

Period	Time Prd	Demand	Deseasonalized Initial	Deseasonalized Centered
1	Q1 2000	98		
2	Q2 2000	106		
3	Q3 2000	109	111.5	112.6
4	Q4 2000	133	113.8	115.0
5	Q1 2001	107	116.3	117.8
6	Q2 2001	116	119.3	120.9
7	Q3 2001	121	122.5	125.0
8	Q4 2001	146	127.5	129.3
9	Q1 2002	127	131.0	132.9
10	Q2 2002	130	134.8	136.4
11	Q3 2002	136	138.0	139.5
12	Q4 2002	159	141.0	142.6
13	Q1 2003	139	144.3	146.4
14	Q2 2003	143	148.5	150.8
15	Q3 2003	153	153.0	
16	Q4 2003	177		

Table 8: Deseasonalized Calculations

$$\overline{D}_{3.5} = \frac{106+109+133+107}{4} = 113.8$$

So that the deseasonalized demand is centered on each period and not between them, each pair of the deseasonalized averages above and below each period must be averaged to get the deseasonalized estimate is as of a certain period, and not between the periods.

$$\overline{D}_{3} = \frac{\overline{D}_{2.5} + \overline{D}_{2.5}}{2} = \frac{111.5+113.8}{2} = 112.6$$

This centered, deseasonalized demand average is shown in the last column of Table 8 where the set of light lines indicate the result of the average of the two numbers, 111.5 and 113.8. The rest of the centered, deseasonalized averages are also shown in this column.

It should be noted that this procedure to deseasonalize the demand is appropriate for seasonal situations where the number of seasons is even. An even number of seasons requires the deseasonalized data be centered. If the number of seasons is odd, as would be the case if the data were broken into say thirteen four-week seasons, then when all of the seasons are averaged, the resulting average would occur on the middle period (in the case of thirteen periods, the seventh period of the data being averaged) and there would be no reason to center the average.

Determining the Initial Forecasting Factors

Once the data has been deseasonalized, finding the level and trend factors is the same as with Holt's trend only model. The deseasonalized averages can be regressed on the period number with the result for this data that

$$L_0 = 100.8 \qquad\qquad T_0 = 3.5$$

Finally, the initial seasonal factors must be determined to complete the model. This requires three steps.

1. Finding an estimate of the straight line fit of deseasonalized demand, $\hat{D}_t$
2. Determining an estimate of the seasonality for each period.
3. Averaging the estimates across all similar seasons.

Step 1 can be done by finding the straight line estimate of deseasonalized demand

$$\hat{D}_t = L_0 + tT_0 \tag{30}$$

For instance, for period 4 the estimate is

$$\hat{D}_4 = 100.8 + 4 \times 3.5 = 114.8$$

The estimate of seasonality from Step 4 for any period is the ratio of the actual demand to the demand forecast

$$\tilde{S}_t = \frac{D_t}{\hat{D}_t} \tag{31}$$

Again, using period 4, this estimate is

$$\tilde{S}_4 = \frac{D_4}{\hat{D}_4} = \frac{133}{114.8} \cong 1.16$$

This number indicates that the actual demand for period 4 is approximately 16% higher than the straight-line deseasonalized fit.

Once an estimate has been calculated for each demand observation (as shown in Figure 5 – with arrows indicating all quarter 4 differences), Step 3 is used to find the initial seasonal factors. For any given "season", all estimates for that season are averaged for an

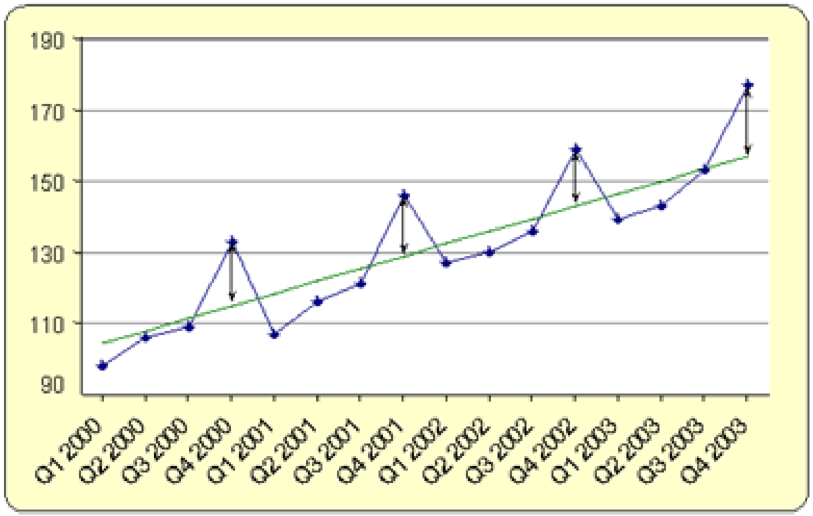

Figure 5: Seasonal Factor for Q4

overall initial seasonal factor for the given season. Thus, one seasonal factor is obtained for each of the *p* seasons by averaging over *k* observations of that season.

$$S_{t\in\{1,2,\ldots,p\}} = \frac{\tilde{S}_t + \tilde{S}_{t+p} + \tilde{S}_{t+2p} + \tilde{S}_{t+3p} + \ldots}{k} \tag{32}$$

For the 4th quarter, this would be

$$S_4 = \frac{S_4 + \tilde{S}_8 + \tilde{S}_{12} + \tilde{S}_{16}}{4} = \frac{1.16 + 1.13 + 1.11 + 1.13}{4} \cong 1.13$$

Doing this for each season, the four seasonal factors are found as

$$S_1 \cong 0.94 \quad ; \quad S_1 \cong 0.96 \quad ; \quad S_1 \cong 0.98 \quad ; \quad S_4 \cong 1.13$$

These calculations are summarized in Table 9.

Forecasting with Winters' Model

Now that the initial level, trend, and seasonal factors have been obtained for Winters' model, the model can be trained and then used to forecast the desired future periods.

						Initial
						Seasonal
Period	Time Prd	Demand		$\hat{D}_t$	$\tilde{S}_t$	Factors
1	Q1 2000	98		104.3	0.94	0.94
2	Q2 2000	106		107.8	0.98	0.96
3	Q3 2000	109		111.3	0.98	0.98
4	Q4 2000	133		114.8	1.16	1.13
5	Q1 2001	107		118.3	0.90	
6	Q2 2001	116		121.8	0.95	
7	Q3 2001	121		125.3	0.97	
8	Q4 2001	146		128.8	1.13	
9	Q1 2002	127		132.3	0.96	
10	Q2 2002	130		135.8	0.96	
11	Q3 2002	136		139.3	0.98	
12	Q4 2002	159		142.8	1.11	
13	Q1 2003	139		146.3	0.95	
14	Q2 2003	143		149.8	0.95	
15	Q3 2003	153		153.3	1.00	
16	Q4 2003	177		156.8	1.13	

Table 9: Seasonal Estimates and Initial Seasonal Factors

To train the model, the initial factors are used to forecast for the first period. In this case, the first forecast is for Quarter 1 of 2000. This forecast is obtained using Equation (27) and

$$F_{t+1} = (L_t + T_t)S_{t+1} \Rightarrow F_1 = (L_0 + T_0)S_1 = (100.8 + 3.5)0.94 \cong 98.0$$

Once this forecast has been made, the assumption is that time moves forward and the period 1 demand is observed to be 98. With the observation of more demand, the level, trend and seasonal factors can be updated as was the case with the previous trend only model. To do this, Equations (32)-(34) are used.

First, the level factor is updated with the assumption that α=0.25 as

$$\begin{aligned} L_t &= \alpha \frac{D_t}{S_t} + (1-\alpha)(L_{t-1} + T_{t-1}) \quad \Rightarrow \\ L_1 &= \alpha \frac{D_1}{S_1} + (1-\alpha)(L_0 + T_0) \\ &= 0.25 \frac{98}{0.94} + 0.75(100.8 + 3.5) = 104.3 \end{aligned}$$

Next, the trend factor is updated with the assumption that β=0.20 as

$$\begin{aligned} T_t &= \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \Rightarrow \\ T_1 &= \beta(L_1 - L_0) + (1-\beta)T_0 \\ &= 0.2(104.3 - 100.8) + 0.8 \times 3.5 = 3.5 \end{aligned}$$

Finally, the seasonal factor for period 1, which happens to be the one used for any first quarter forecasts, is updated. The smoothing parameter is γ=0.15.

$$
\begin{aligned}
S_{t+p} &= \gamma \frac{D_t}{L_t} + (1-\gamma)S_t \Rightarrow \\
S_5 &= \gamma \frac{D_1}{L_1} + (1-\gamma)S_1 \\
&= 0.15\frac{98}{104.3} + (1-0.15)0.94 = 0.94
\end{aligned}
$$

Note that this update didn't change any of the factors and this is because the forecast was very accurate for the first period. Once the parameters have been updated, Equation 27 can be used once again to forecast the next period, period 2. The rest of the computations for this forecasting and updating are shown in Table 10.

				α	β	γ			
				0.25	0.2	0.15			
Period	Time Prd	Demand		Level	Trend	Seasonal	Forecast		Error
				100.8	3.5				
1	Q1 2000	98		104.3	3.5	0.94	98.0		0.0
2	Q2 2000	106		108.4	3.6	0.96	103.5		-2.5
3	Q3 2000	109		111.9	3.6	0.98	109.8		0.8
4	Q4 2000	133		116.0	3.7	1.13	130.5		-2.5
5	Q1 2001	107		118.2	3.4	0.94	112.5		5.5
6	Q2 2001	116		121.4	3.3	0.96	117.1		1.1
7	Q3 2001	121		124.4	3.3	0.98	122.1		1.1
8	Q4 2001	146		128.0	3.4	1.13	144.6		-1.4
9	Q1 2002	127		132.5	3.6	0.93	122.8		-4.2
10	Q2 2002	130		135.9	3.5	0.96	130.8		0.8
11	Q3 2002	136		139.3	3.5	0.98	136.3		0.3
12	Q4 2002	159		142.2	3.4	1.13	161.9		2.9
13	Q1 2003	139		146.2	3.5	0.94	136.6		-2.4
14	Q2 2003	143		149.5	3.5	0.96	143.9		0.9
15	Q3 2003	153		153.8	3.6	0.98	149.6		-3.4
16	Q4 2003	177		157.2	3.6	1.13	178.2		1.2
17	Q1 2004					0.94	**151.2**		
18	Q2 2004					0.96			
18	Q3 2004					0.98			
20	Q4 2004					1.13			

Table 10: Forecasting and Updating for Jackets-And-Such

Summary

The prior sections have provided the reader with an introduction to a number of fundamental approaches and models to time series forecasting and illustrated their computational process. Some forecast models like Winters' are complicated, involving numerous mathematical equations with the inherent required notation to manage the needed computations. But as complicated as they might be, using these statistical models can help reduce forecast errors to manageable levels without significant levels of everyday human interaction. These models are designed to remove systematic error and can be helpful in doing just that when implemented correctly. While more elaborate models like ARIMA and X11 have been proposed[3], the set described above have proved to be the primary forecasting tools used in practice.

Practice has also shown that forecasts, no matter how sophisticated a model employed, will still have forecast errors. Perfect forecasts, while a laudable goal, can't be attained because random behavior and dynamic change is always present. The solution? Human input is a critical component to test for reasonableness and handle unforeseeable events. Therefore, the forecast system design needs to combine human oversight management with statistical forecasting models on computer-based systems like SAP's R/3 system, so that management time can be spent most productively on the numerous tasks within the supply chain.

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[3] The interested reader can use the citations listed in the references to explore their features.

Time Series Forecasting Problems

1. Using the data above in Table 4 for Bike 3023, forecast demand using the BES model, but with an α=0.4. Compare this forecast to the example with an α=0.2.

2. Using the data above in Table 4 for Bike 3023, forecast demand using a five-period moving average and a five period weighted moving average for periods 7 through 13. For the weighted moving average, use the weights 0.5, 0.4, 0.3, 0.2, and 0.1. Compare these two forecasts to the two BES models for Bike 3023, especially with respect to the MAD, MSE, Bias, and TS for periods 7 through 12.

3. Using the data above in Table 4 for Bike 3023, fit an additive trend model to the data and forecast periods 7 through 15. Compare this forecast model to the two BES models and the two MA models in problems 1 and 2 by commenting on the errors.

4. Table P4 contains two years of demand information for a recently introduced food product. Use a additive trend model to forecast demand for this new product for the first three months of 2004.

Month	Year	Demand	Month	Year	Demand
Jan	2002	155	Jan	2003	410
Feb	2002	190	Feb	2003	415
Mar	2002	200	Mar	2003	450
Apr	2002	205	Apr	2003	455
May	2002	210	May	2003	540
Jun	2002	250	Jun	2003	525
Jul	2002	300	Jul	2003	490
Aug	2002	300	Aug	2003	520
Sep	2002	330	Sep	2003	550
Oct	2002	370	Oct	2003	575
Nov	2002	370	Nov	2003	620
Dec	2002	375	Dec	2003	655

Table P4: Demand for New Food Product

5. Table P5 contains four years of demand information for item X503A2. It is believed that since the demand shows some seasonal pattern that Winters' Model is the forecasting model that should be used for this item. Forecast 2004 Quarter 1 demand for X503A2 based on the forecast model fit with the first four years of data. Use α = 0.4, β=0.3, and γ=0.2 as smoothing parameters.

Year	Qtr	Demand	Year	Qtr	Demand	Year	Qtr	Demand	Year	Qtr	Demand
2000	Q1	2000	2001	Q1	3000	2002	Q1	5000	2003	Q1	5000
2000	Q2	4000	2001	Q2	5000	2002	Q2	5000	2003	Q2	7000
2000	Q3	12000	2001	Q3	15000	2002	Q3	16000	2003	Q3	20000
2000	Q4	16000	2001	Q4	18000	2002	Q4	20000	2003	Q4	22000

Table P5: Quarterly Demand Data for X503A2

Month	Year	Demand		Month	Year	Demand		Month	Year	Demand
Jan	2002	50		Jan	2003	47		Jan	2003	42
Feb	2002	53		Feb	2003	46		Feb	2003	45
Mar	2002	134		Mar	2003	129		Mar	2003	123
Apr	2002	243		Apr	2003	225		Apr	2003	217
May	2002	207		May	2003	246		May	2003	201
Jun	2002	89		Jun	2003	65		Jun	2003	66
Jul	2002	77		Jul	2003	56		Jul	2003	45
Aug	2002	164		Aug	2003	143		Aug	2003	138
Sep	2002	178		Sep	2003	161		Sep	2003	141
Oct	2002	94		Oct	2003	85		Oct	2003	93
Nov	2002	57		Nov	2003	49		Nov	2003	51
Dec	2002	44		Dec	2003	56		Dec	2003	45

Table P6: Monthly Demand Data for Rain Jacket

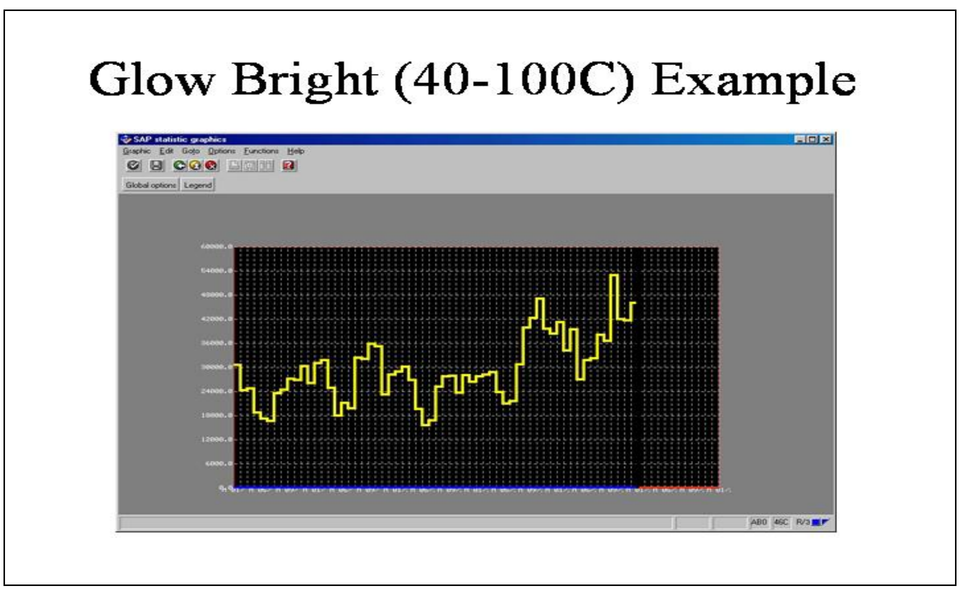
6. Table P6 contains three years of monthly demand information for a popular classic rain jacket. Forecast the first six months of demand for this jacket based on forecast model fit with the first four years of data. Use $\alpha = 0.4$, $\beta=0.3$, and $\gamma=0.2$ as smoothing parameters.

Forecasting with SAP R/3

Introduction and Background

The prior section presented a tutorial on basic time series forecasting logic, procedures and performance measures. While we could program these procedures using tools like Visual Basic or Excel spreadsheets, there are several commercial packages available to support business planning. This section illustrates how to employ the SAP R/3 system to conduct forecasting. It shows how to load data, define forecast parameters, obtain forecasts, and review the results from R/3's forecasting process.

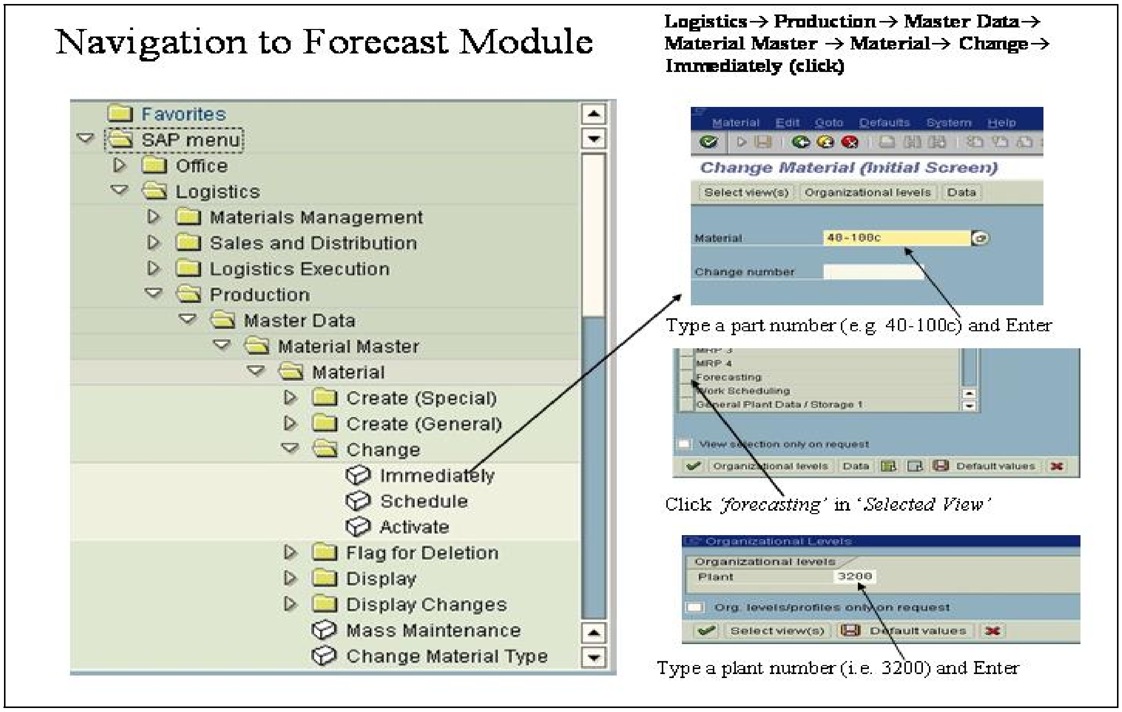
The Glow-Bright Corporation case (included in a later section) provides an opportunity to demonstrate the forecasting system within the SAP R/3 system. Below is an example plot of sales in R/3 for part number 40-100C of Glow-Bright. Note that the data exhibits seasonality and an upward trend in historical sales. The R/3 forecasting system employs a time series analysis approach to forecasting, and as such, attempts to find a pattern over time in the historical database, and then extends this pattern into the future. As discussed above, there are a number of models that users may chose to attempt to match historical patterns. Therefore, the system must first have historical data to do the time series analysis for the forecasts.



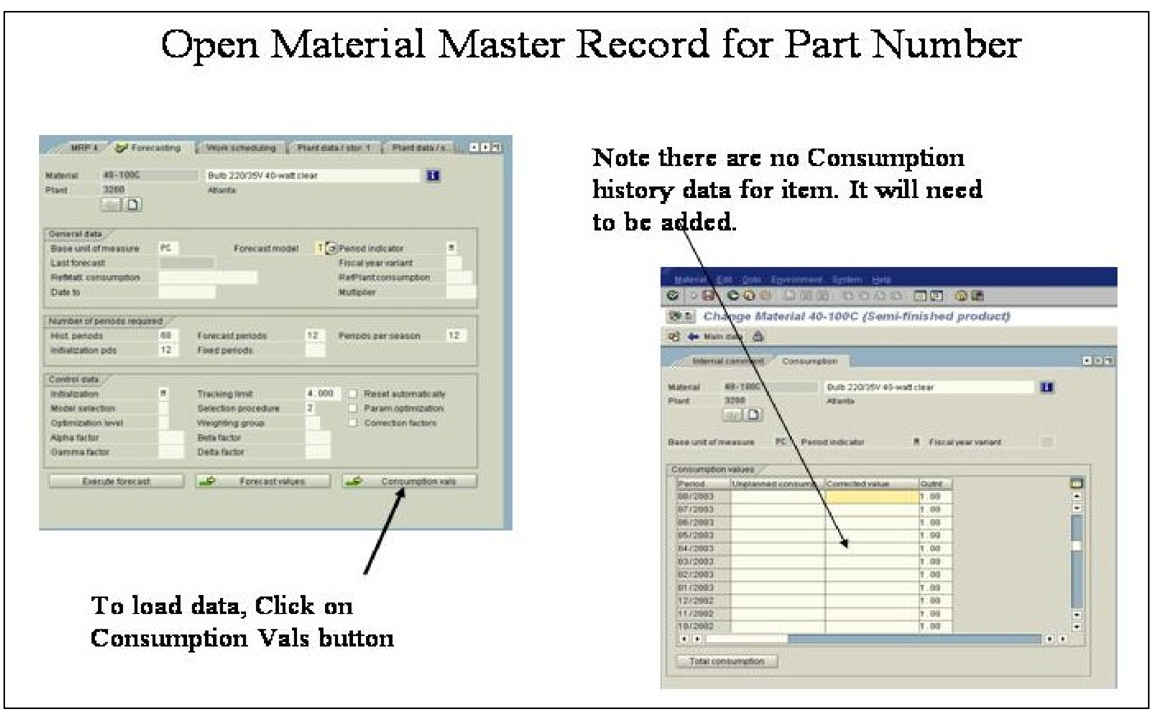
Loading Historical Data

The first step to using the forecast feature of R/3 requires populating the 'Material Master' with historical sales data. Since the system used in a learning environment is not an active system with "real" sales data, this historical data must be entered before any forecasting can be done. To enter this data, navigate through the Dynamic Menu within

R/3 down to the plant level by making the appropriate entries, as shown below. This will eventually lead to the ‘Forecasting’ tab within the ‘Material Master’ which allows one to use the Forecast Module.



Next, open the ‘Forecasting’ tab of the record for part 40-100C and click on the *Consumption Vals* button. This opens the table of historical data, as shown below. Note that the first time this table is opened the record will be empty.



One of the most important issues in using the R/3 forecasting module is the time orientation of the data. This arises because the R/3 system is an operational system with a running clock. Any time you use the system, the system clock will be the current time and date. Thus, the first thing that has to be determined is the current R/3 system time clock date. This will be the time origin reference for forecasting. Another important issue is that the historical data needs to be sequenced from <u>most recent</u> to <u>oldest</u>. The Glow Bright historical sales data is organized in an oldest-to-most recent format – as shown below – and this is the opposite of what is needed.

Adding Data History:

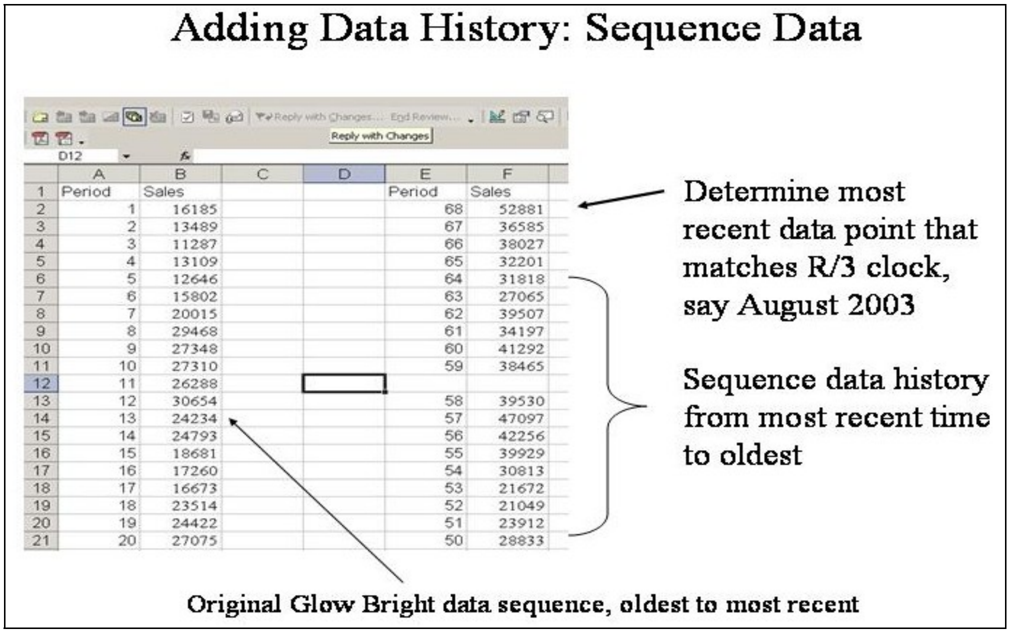
Determine Data Timeline and Origin

Table 1	40-100C	Unit	Sales	(Cartons)		
Month	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**
1	16,185	24,234	31,768	30,117	28,228	34,197
2	13,489	24,793	24,894	26,885	28,833	39,507
3	11,287	18,681	18,070	19,686	23,912	27,065
4	13,109	17,260	21,138	15,607	21,049	31,818
5	12,646	16,673	19,750	16,795	21,672	32,201
6	15,802	23,514	32,474	25,172	30,813	38,027
7	20,015	24,422	32,053	27,731	39,929	36,585
8	29,468	27,075	35,923	27,951	42,256	52,881
9	27,348	26,793	35,248	23,729	47,097	41,933
10	27,310	30,279	23,315	28,034	39,530	41,701
11	26,288	26,118	28,252	26,363	38,465	46,017
12	30,654	30,986	28,879	27,675	41,292	45,027

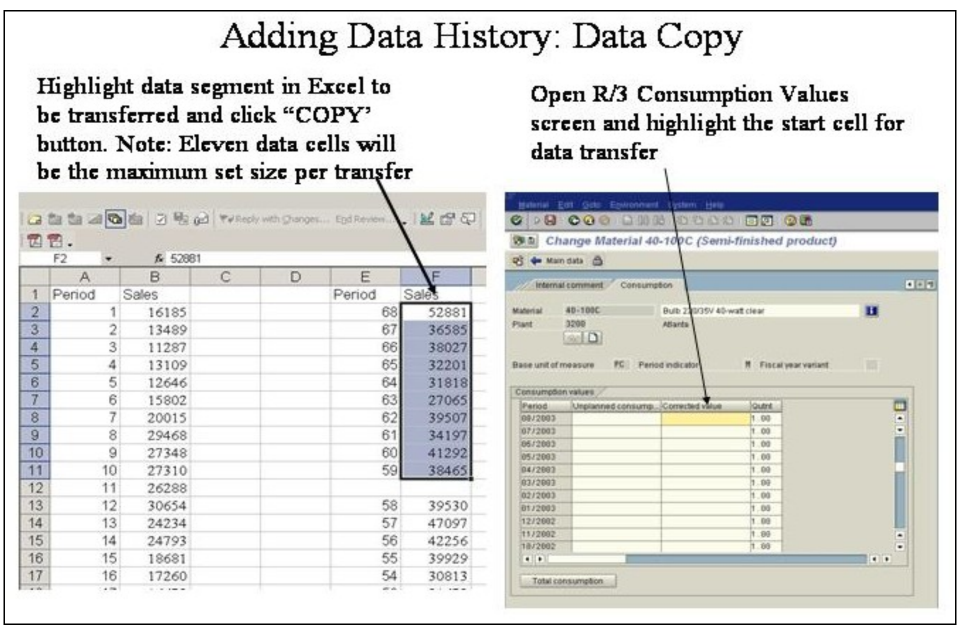
Need to know current time point for forecast origin that is established by SAP R/3 system clock , e. g. August 2003, and eliminate the remaining data from use

Glow Bright data in sequence of oldest to most recent. However, R/3 system wants data in most recent to oldest sequence.

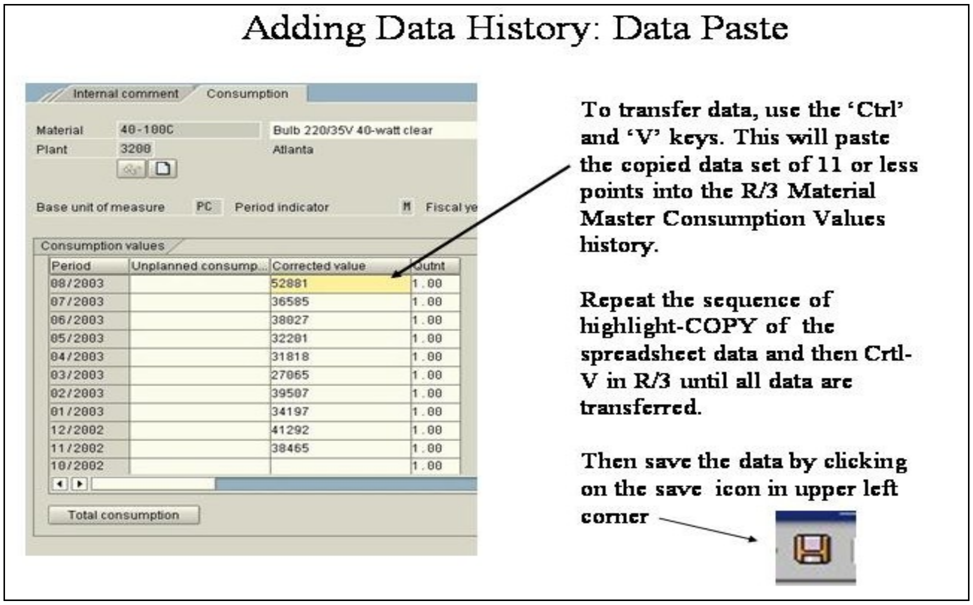
Assume that the current R/3 system time is August of 2003. This will be assumed to be the time origin point for the sales history. That is, the last month of the sales data should be August of 2003. Next, the data needs to be re-sequenced from <u>most recent</u> to <u>oldest. This can be done very easily</u> in Excel, starting with the data from August 2003 (Period 68 with a demand of 52,881).



The data is then transferred to the R/3 system by using the Excel 'COPY' command (Note that this is the only way of transferring data from Excel to the R/3 system). This data transfer must be done by copying ***no more than eleven cells at a time***. Thus, one needs to go to the Excel sheet and highlight the first 11 cells of data, and then go to the R/3 'Consumption' Page and highlight the first cell in the "Corrected Values" column, and paste the first 11 historical data figures into R/3. Please note that you ***have to*** use CTRL-V (simultaneously pressing the CTRL key and the V key) to paste.



Continue transferring data from the Excel sheet by repeating the 'COPY' command for the appropriate data (again, remembering to highlight no more than eleven cells at a time) and going to the R/3 ‘Consumption’ Page and highlighting the next empty cell in the “Corrected Values” column before placing the data with the CTRL-V entry. When all the data have been transferred, it should be saved in the system by clicking the save icon in the upper left corner of the screen (This is the orange disk icon).



Forecasting With SAP R/3: Steps and Input Requirements

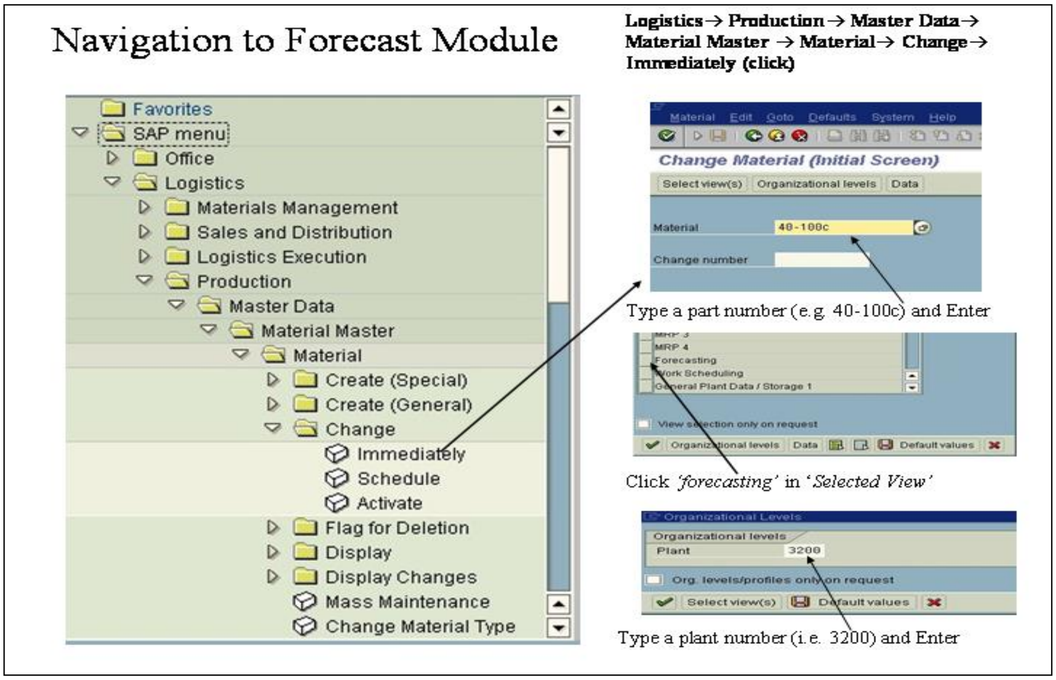
With the historical data loaded into the material master forecasting record for an item, two forecasting options are available to the user:

- **User Selection Approach** (USA) – all forecast parameters and models are manually entered by user.
- **System Selection Approach** (SSA) – a set of specific forecast parameters and models (e.g., smoothing constant values, simple versus enhanced smoothing, etc.) are determined by R/3 system and the remainder is user determined.

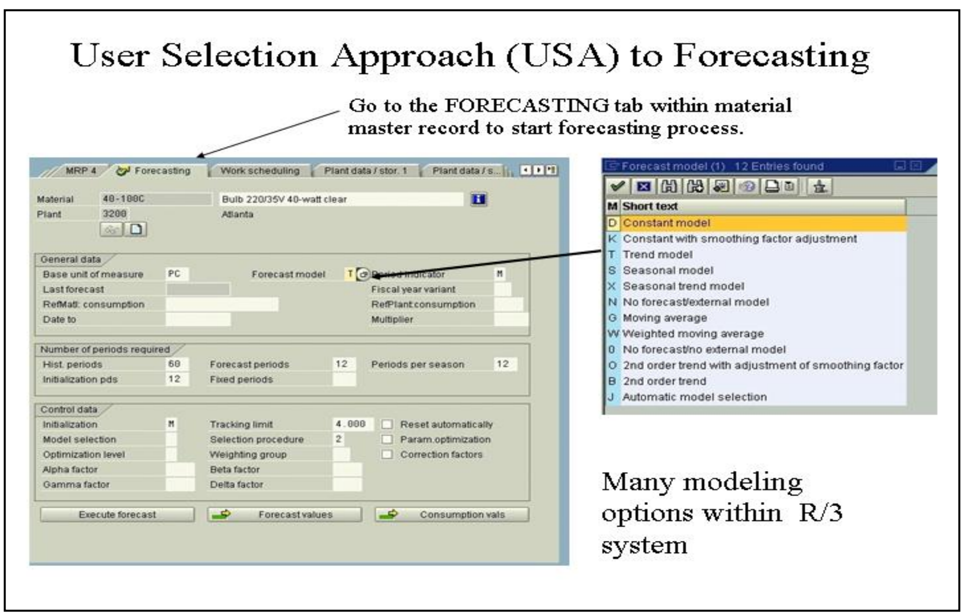
These two approaches are illustrated next.

User Selection Approach to Forecasting

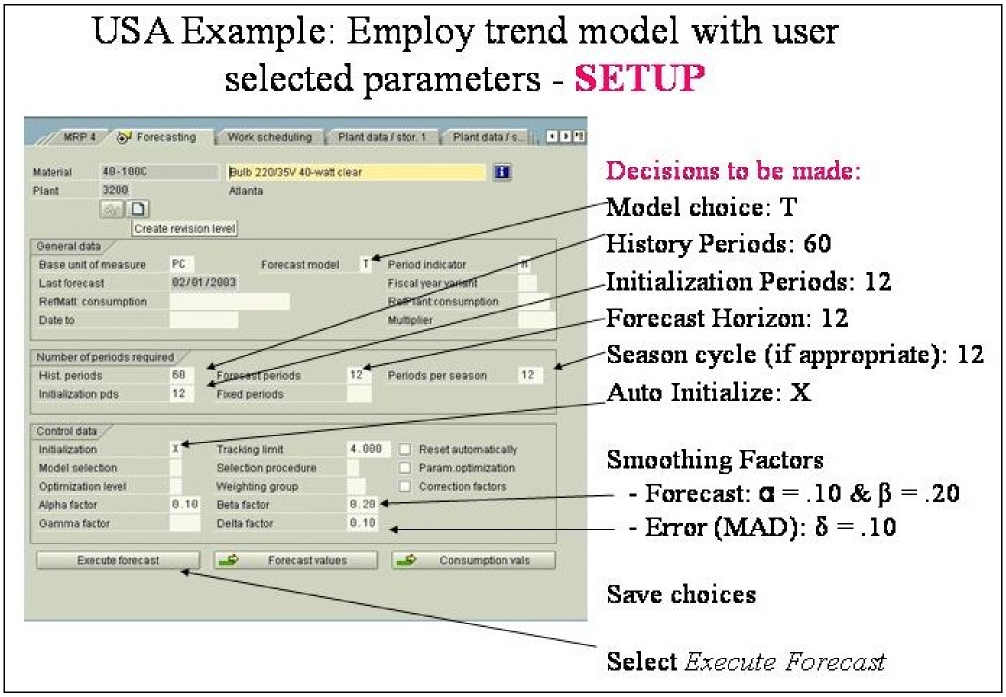
First, there is a need to return to the ‘Forecasting’ tab within the Dynamic Menu of the R/3 system as shown below.



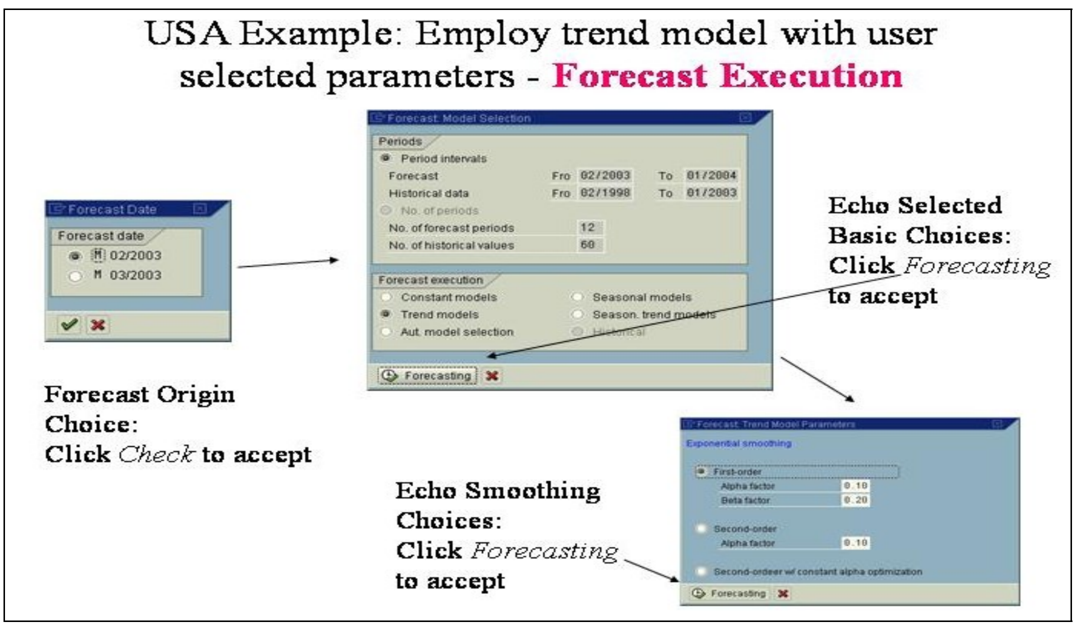
Once the 'Forecasting' tab has been reached, the forecasting model must be chosen. There are many forecasting models within R/3 and clicking on the dropdown button beside "Forecast model" presents the options, as shown below. The user approach requires the analyst to determine and select the model that is appropriate for the data.



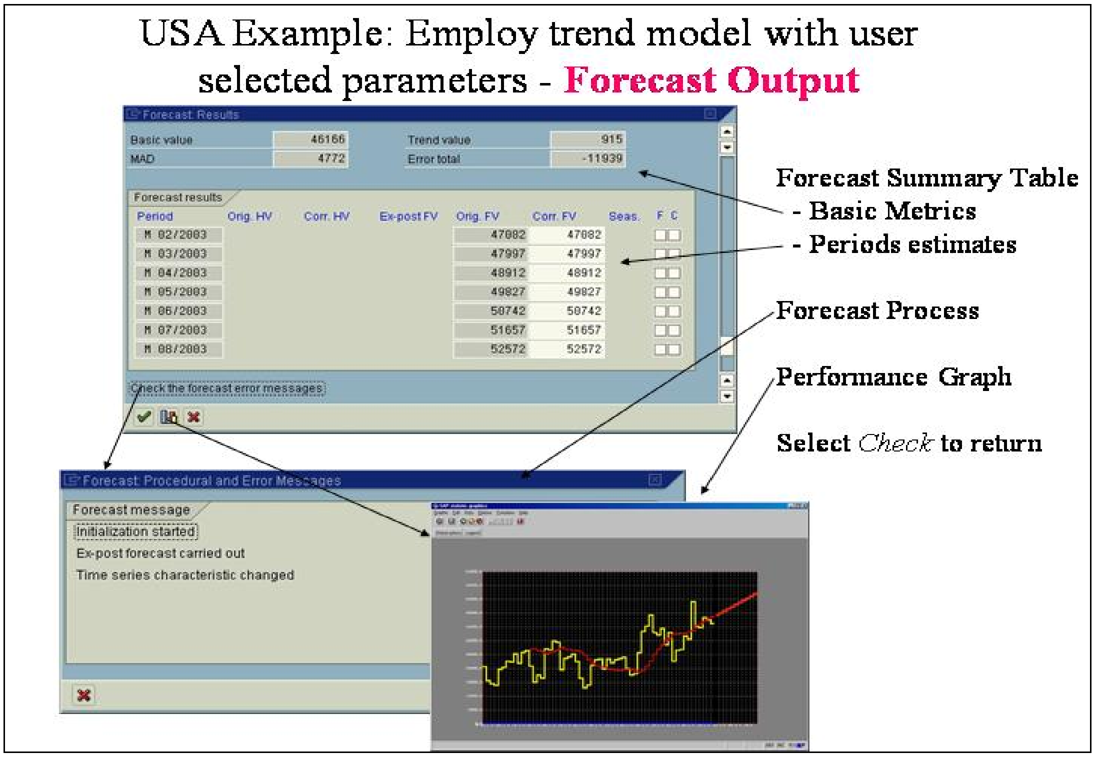
Besides selecting the desired forecasting model, the user also needs to input the forecasting parameters discussed earlier in this document. These requirements are illustrated below. Once the parameters have been entered, the *Save* button (The orange disk icon) is used before proceeding with the forecast.



When the forecast setup is complete, the *Execute Forecast* button is used to initiate the forecast process. The forecast execution requires establishing the forecast time origin and confirming that the correct parameters are set, as shown with the following screen shots.

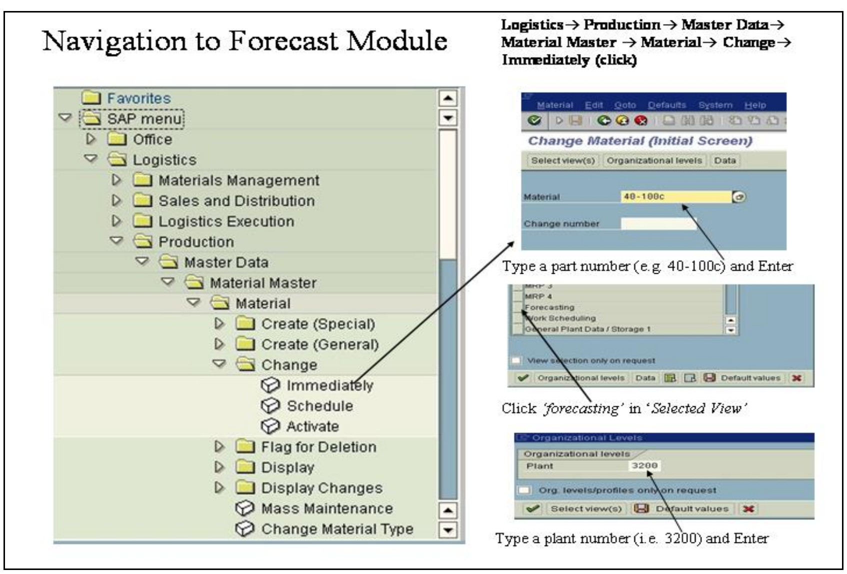


With the forecasting execution completed, the Forecast Results are displayed. The results provide the forward looking forecasts, basic error metrics and messages. Clicking on the chart button provides a plot of the historical demand and forecasted data.

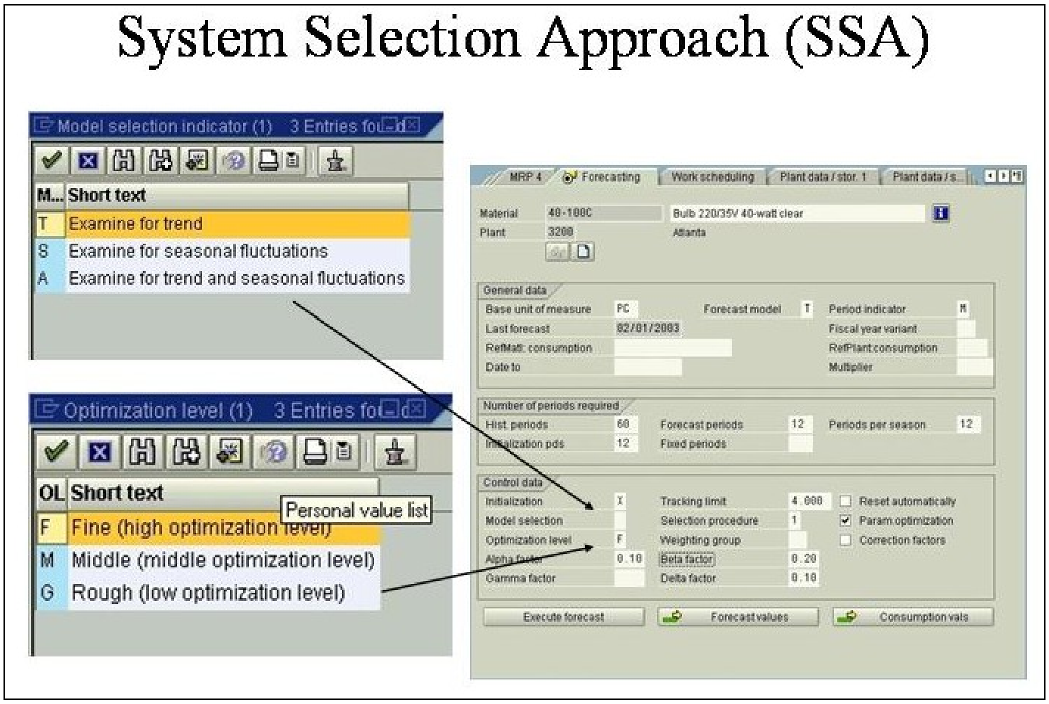


System Selection Approach to Forecasting

First, as with the last approach, there is a need to return to the ‘Forecasting’ tab in the Dynamic Menu. This is done through the ‘Material Master’ as highlighted below.



Within the R/3 system, there are a set of features that allow the system to determine the appropriate forecast model (e.g., inclusion of seasonal factors) and the associated smoothing values. As shown below, the user determines which potential model options are available and what level of refinement is desired.



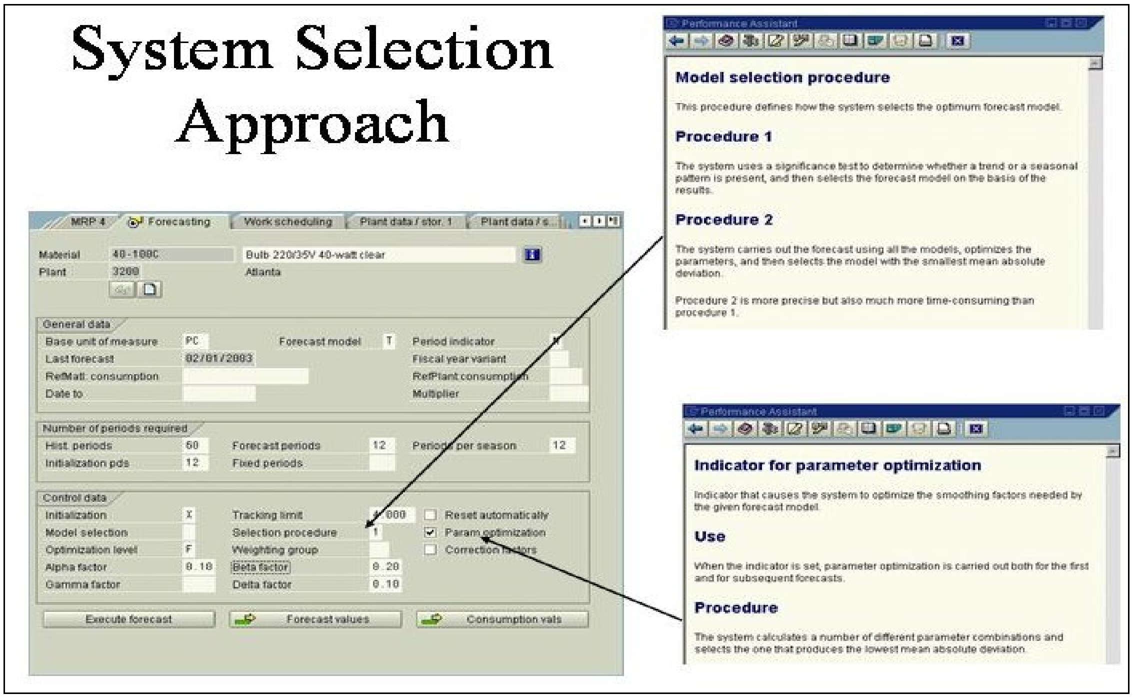
To invoke SSA, the user selects the option the system will use to determine the forecast model and parameter values. The figure below identifies the appropriate entries in the 'Forecasting' tab page.

For model selection, the options are:

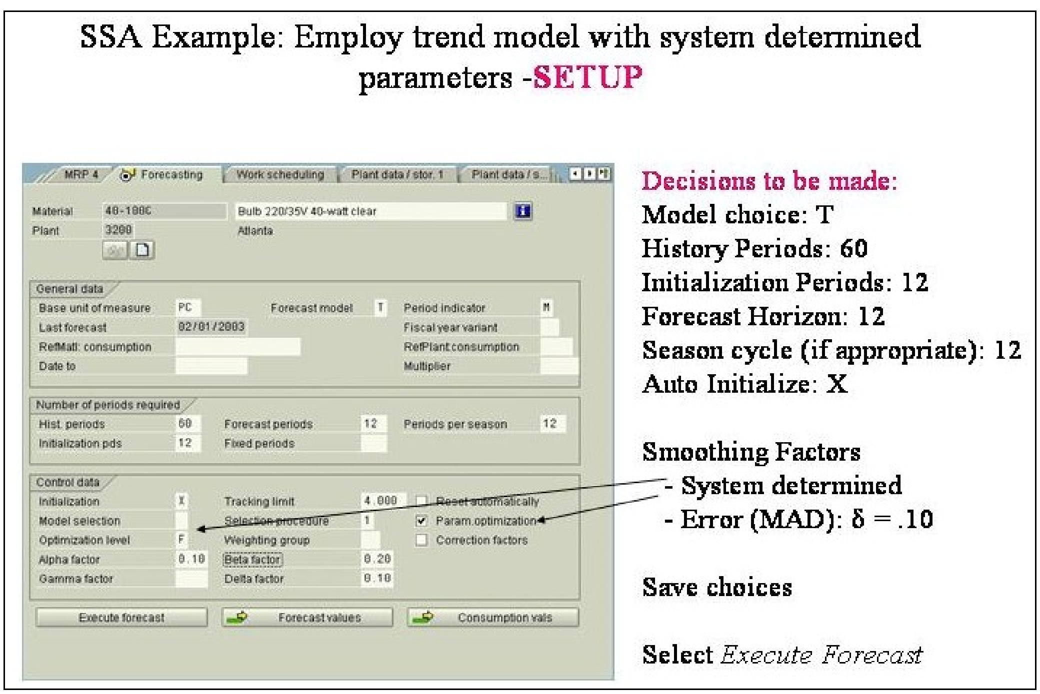
Procedure 1 -The system uses a significance test to determine whether a trend or a seasonal pattern is present, and then selects the forecast model on the basis of the results.

Procedure 2 - The system carries out the forecast using all the models, optimizes the parameters, and then selects the model with the smallest mean absolute deviation.

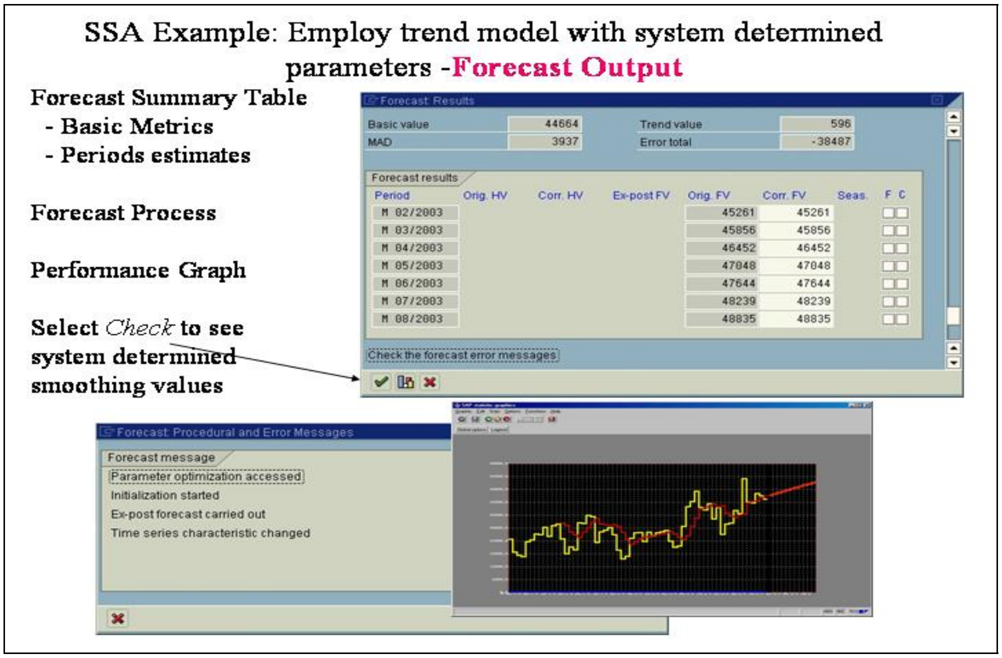
For Parameter Optimization, the set indicator (check mark) causes the system to determine the best smoothing factors needed by the given forecast model to minimize errors. The system calculates a number of different parameter combinations and selects the one that produces the lowest mean absolute deviation.



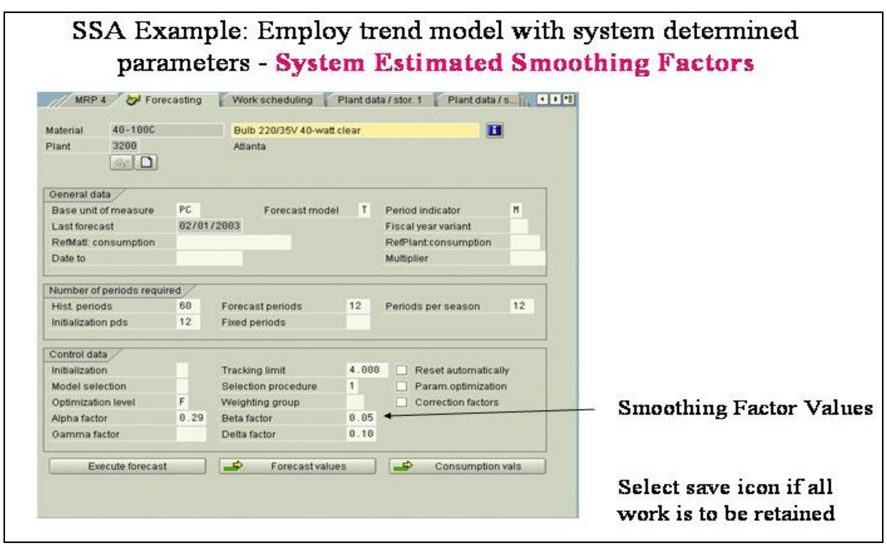
While the R/3 system will determine a set of forecast parameter components, the user still must provide a number of inputs, as shown below, to complete the forecast preparation process. With the required user input supplied, click the *Execute Forecast* button to proceed. The time origin and echo check will take place as illustrated in the previous procedure. If satisfied with the input, click the *Forecast* button for forecast execution.



The Forecast Results report follows the structure as described earlier, with the same features. Check the 'Forecast message' tab to determine what has occurred during forecast execution. To see the optimal parameter values, click the *check* button.



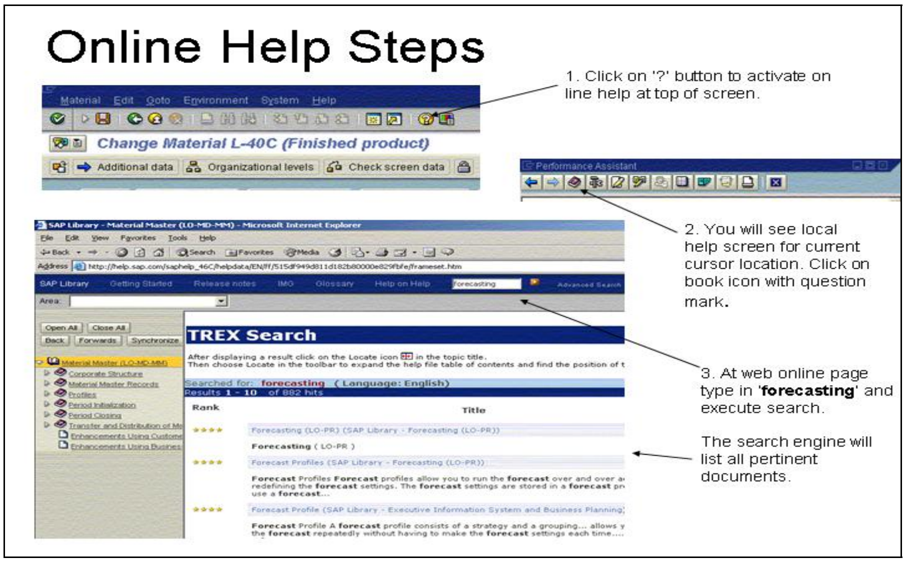
For the Glow-Bright data example, the model included trend and determined the best alpha and beta values, shown below. If satisfied with results, click the *save* button to save the forecast values and all forecast parameter settings for future use.



Summary

This section has demonstrated the steps required to conduct time series forecasting using the SAP R/3 system. It illustrated how to load data into the material master record, highlighted the required forecast parameter options that are available to the user and showed the forecast execution steps.

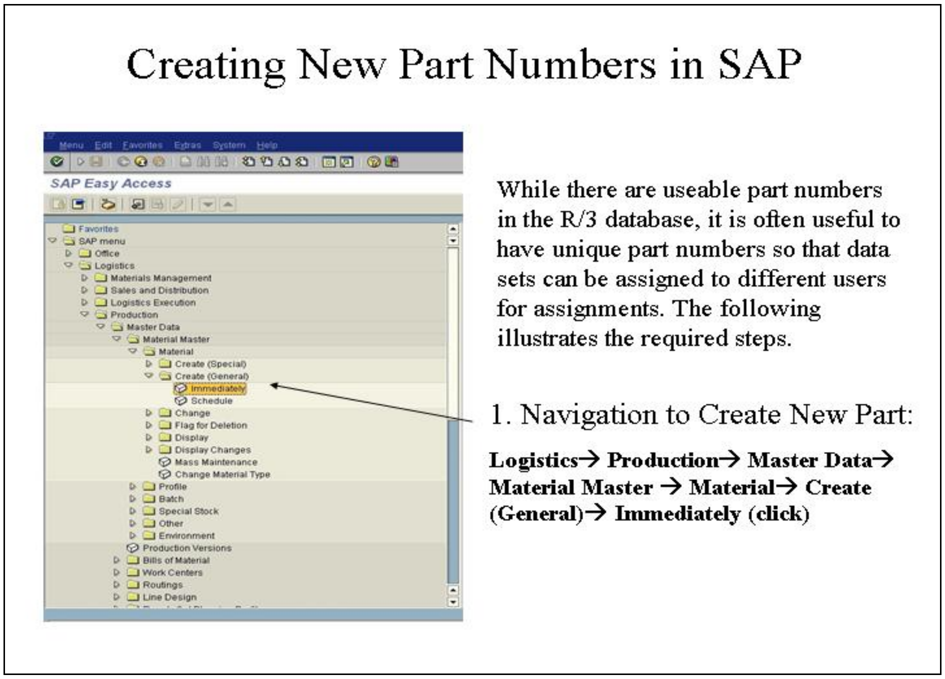
For more information about the SAP R/3 forecast module, the interested reader can use the online help system. It provides more extensive documentation of system features and requirements.



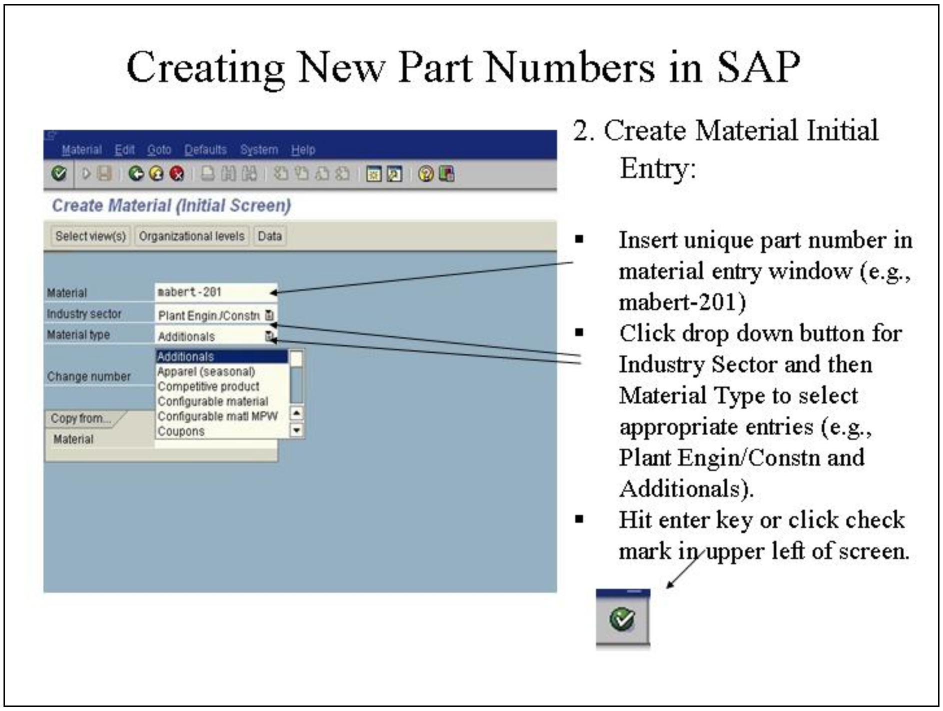
Creating Part Numbers

While the SAP R/3 system has about 20 blank part numbers that can be used for forecasting, it can be advantageous to create unique part numbers for use. The exhibits below illustrate the required steps:

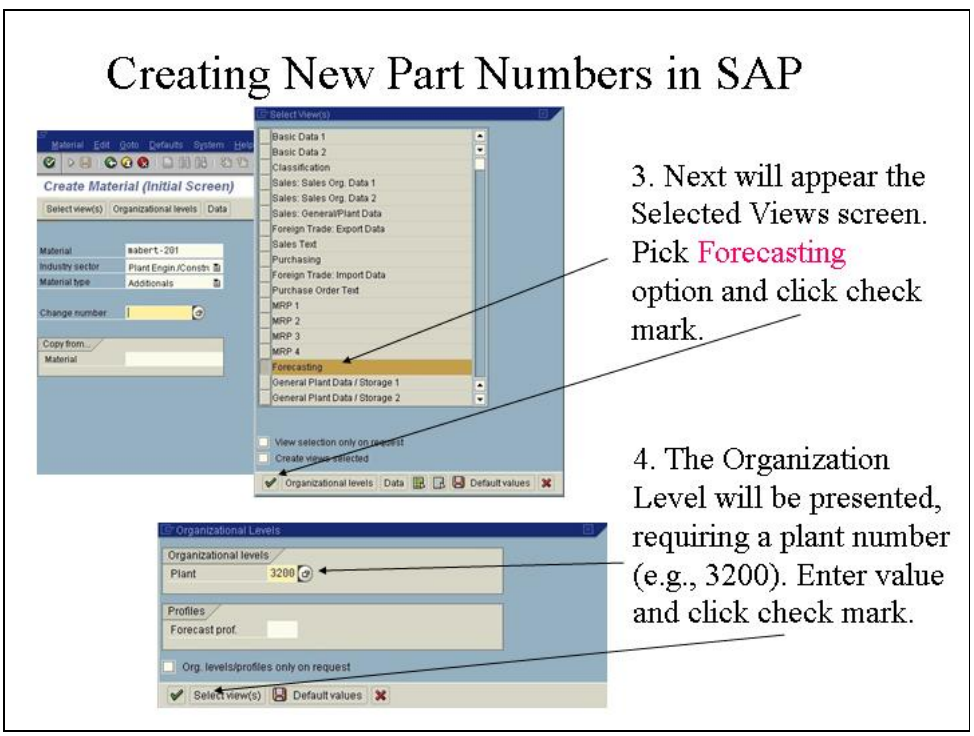
Navigate to Create Screen to initiate creation process.



Enter initial required data of unique part number. Using drop down menus for industry sector and material type, select appropriate options and click check mark.

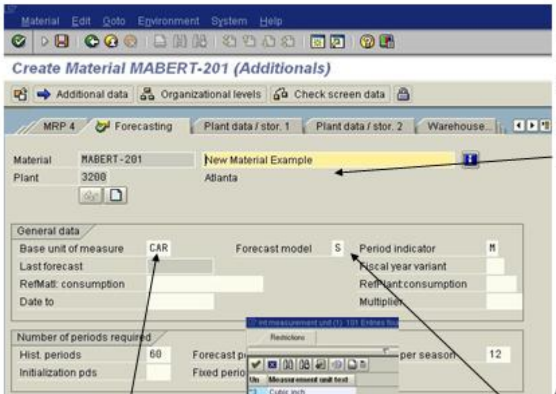


Assign part number to Forecasting and Plant master data set.



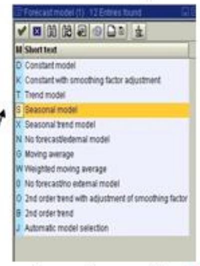
Complete minimal data requirements for master.

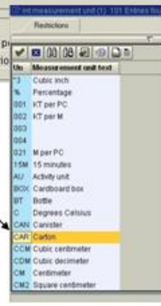
Creating New Part Numbers in SAP



5. At the Forecasting Tab screen three data entries are minimum required entries:

a. Enter a descriptive name





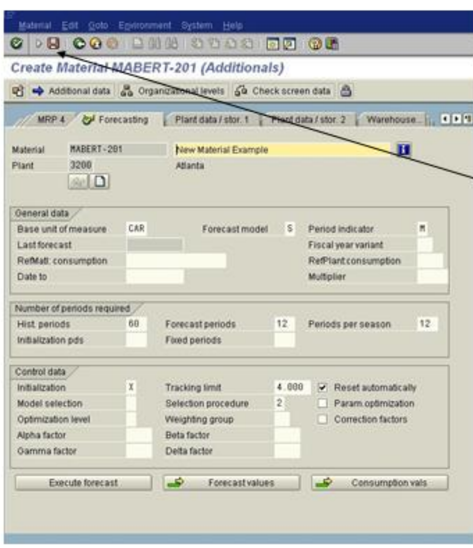
b. Using drop down for Base unit of measure, select appropriate option

c. Using drop down for Forecast model, select appropriate option

d. Click check mark →

With entries complete, save new part master for future use.

Creating New Part Numbers in SAP



6. Once the three minimum data entries have been complete, the record should be retained by clicking the save icon (Disk) in upper left corner.

Note: If desired, other screen entry options can be input at this point and saved.

Glow-Bright Corporation Case[4]

John Hartness, plant manager for Glow-Bright Corporation's Atlanta plant, sat at his desk reviewing recent production reports for the last accounting period. According to the reports, the plant had been operating near the highest output level in its history for their model 40-100C, a 40 watt clear incandescent light bulb. Glow-Bright's other product lines were also experiencing strong sales.

As John sat there feeling proud of the increased output that the plant had attained, the phone rang and broke into his thoughts. It was Dan Martin, vice president of manufacturing, calling for his weekly check-in with John to discuss operations at the plant.

Looking over his production reports, John turned to the warehouse reports to refresh some points in his mind. "Dan, the warehouse reports have shown excessive costs. The Atlanta warehouse has had to purchase another forklift and hire an operator for it. Thompson, at the Chicago facility, has indicated that they have had to rent temporary space at the public warehouse around the corner. We may have to expand or lease more space."

A few seconds of silence occurred at the other end of the phone. Then Martin responded, "Before we consider investing for expansion or committing ourselves to a lease, we must be certain that the increased demand is genuine. In the next week, discuss with marketing what demand we can anticipate for the 40-100C bulb in the future. Keep in mind when you talk to them that those marketing forecasts are never right. It sounds like we need to act on this issue quickly, so let me know your opinion as soon as possible."

After hanging up the phone, Hartness looked at his watch. It was almost noon. He got up, pulled his coat off the hook, and headed out of his office door for a luncheon meeting with the local Kiwanis Club planning committee. As he went through the outer office, he stopped to talk to his secretary, Emma Castaro. "Emma, will you please go through our past sales records and list the units sold in each period for the last six years for the 40-100C bulb. Also, bring me the forecast reports supplied by marketing for those same months. Please have them on my desk this afternoon, so that I can review what has been happening."

Later that afternoon, Emma came into Hartness' office with the sales and forecast data. As John looked over the sheets, shown in Tables 1 and 2, Emma said, "I called marketing and asked for the forecasts, which production planning uses. They sent over this report." She handed John the forecasts (Table 2) for the same period, as compiled by the marketing department. Attached to the forecast report was a copy of the standard form letter (Exhibit 1) from Harold Wilson, vice-president of marketing, to the district sales managers. He was requesting the annual sales force forecasts for the coming year. Emma indicated it was sent to give Hartness background on how the annual forecast was developed.

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[4] Case developed by Vincent A. Mabert, Indiana University. Revised 8/23/2003

Basically, the sales force is polled as to their expectations for the coming year. These forecasts are made at the end of each year. The district and home office managers then make adjustments to remove any bias that the salesmen have. The forecasts are then given to the production department to use in laying out the manufacturing schedule.

John looked at the actual and forecast sales volume, Tables 1 and 2. He pulled his new Cross pencil from his shirt pocket and started checking the errors between what was forecasted and the actual sales.

Then the telephone rang. It was Roger Steel, director of production planning. He called to find out where John was. Hartness was already half an hour late for the weekly plant meeting of department heads. John hung up the phone and headed for the conference room. As he went down the hall, he knew it would be a long night. He needed to get the new laptop PC from the Industrial Engineering Department to assist in analyzing the forecast and actual sales volume.

Company Background

Glow-Bright manufactures multiple lighting product lines at the Atlanta plant: both incandescent (25, 40, 60, 75 watts, etc.) and florescent light (10, bulbs - 10, 20, and 40 watts) in various wattage levels and frosting finishes for residential applications. The Atlanta twelve-acre site has two plants, employing about 850 employees. Plant 3200 produces incandescent bulbs, while Plant 3400 assembles florescent lights.

Glow-Bright distributes its light bulbs through regional warehouses to wholesalers, major box retailers like Lowes and Home Depot, and discount chains. The wholesalers then sell directly to retail outlets like hardware stores.

The National Lighting Institute (NLI) has estimated that sales of lights are broken into three categories: residential lighting, commercial lighting and specialty applications. The sales seem to be linked to the general economic conditions of the country. NLI routinely reports the sales level for the lighting industry. Table 3 lists the industry experience for the last six years.

Study Guide Questions

1. Evaluate the current forecasting procedures at Glow-Bright. Are they adequate for manufacturing needs?

2. How would you design and implement a forecasting system at Glow-Bright?

GLOW-BRIGHT CORPORATION
Atlanta, GA
(Exhibit 1)

October 20, 2002

To: District Managers
C.B. Ernst - Tulsa
R.E. Edmunster
Beach Associates
Haffer & Allison - Portland
Haffer & Allison - Seattle
Bill Tellson
Alloy Products Company

Subject: Unit Sales Product Forecast for Next Year

This is the time of year that we are making plans for next year's production. So that we can meet your customer requirements and, at the same time, operate our facilities at the most efficient level, we need your very best efforts in estimating sales by product line. Please complete the attached forms and return to us by December 10.

You should take as positive an attitude as possible to get the most meaningful information. While it is true that in many cases customers will tell you that they do not know what their requirements will be, there may be other individuals within the company who can give you better information. Keep in mind that the firm itself must make its own plans in advance and conduct its own surveys.

Among the things that you might want to consider in addition to asking key individuals within the company are:

a. The general forecast of economic conditions in your territory
b. The projected housing starts and commercial construction for the area.
c. Whether or not you feel Glow-Bright will be getting increases, decreases, or the same share of the business from specific customers.
d. Whether or not you will "break in" with new customers.
e. Whether or not you will lose customers because of problems.

For the last couple of years, we have been caught short, with resulting loss of business because of poor deliveries. In all cases, we would have been current on deliveries had the forecast been accurate. It is to our benefit to consider this a major assignment.

Harold Wilson: mrm

Table 1: 40-100C Unit Sales (Cartons)

Month	1998	1999	2000	2001	2002	2003
1	16,185	24,234	31,768	30,117	28,228	34,197
2	13,489	24,793	24,894	26,885	28,833	39,507
3	11,287	18,681	18,070	19,686	23,912	27,065
4	13,109	17,260	21,138	15,607	21,049	31,818
5	12,646	16,673	19,750	16,795	21,672	32,201
6	15,802	23,514	32,474	25,172	30,813	38,027
7	20,015	24,422	32,053	27,731	39,929	36,585
8	29,468	27,075	35,923	27,951	42,256	52,881
9	27,348	26,793	35,248	23,729	47,097	41,933
10	27,310	30,279	23,315	28,034	39,530	41,701
11	26,288	26,118	28,252	26,363	38,465	46,017
12	30,654	30,986	28,879	27,675	41,292	45,027

Table 2: 40-100C Forecast Units (Cartons)

Month	1998	1999	2000	2001	2002	2003
1	27,000	31,000	32,000	34,000	35,000	35,000
2	27,000	31,200	32,000	34,000	35,000	35,000
3	29,000	31,800	33,000	34,000	35,000	36,000
4	29,000	31,400	34,000	34,000	35,000	38,500
5	29,000	31,200	34,000	35,500	36,000	38,500
6	30,000	31,000	33,000	35,400	36,000	38,500
7	31,000	30,800	32,500	36,000	35,000	38,000
8	32,000	30,600	32,500	33,000	35,000	37,000
9	29,000	30,400	32,500	33,000	35,000	36,000
10	29,000	30,000	32,500	32,400	35,000	37,000
11	28,600	30,000	32,000	32,000	34,000	36,000
12	28,000	30,000	32,000	32,000	34,000	36,000

Table 3: Lighting Sales Estimates for NLI ($ 000)

Month	1998	1999	2000	2001	2002	2003
1	67,477	90,462	110,862	102,738	136,985	172,154
2	65,815	91,846	118,708	83,354	124,892	168,369
3	69,623	97,177	111,008	90,208	121,169	176,662
4	96,200	132,123	148,692	126,062	176,985	223,954
5	117,508	165,669	174,092	149,862	216,254	241,777
6	135,662	161,877	176,985	148,985	222,769	252,185
7	138,885	153,331	172,031	152,754	222,323	256,238
8	135,138	152,954	158,815	160,985	222,231	245,769
9	136,469	154,192	149,062	160,062	227,062	244,954
10	138,554	153,323	152,431	155,846	226,708	249,969
11	138,000	153,831	155,700	161,215	210,900	236,146
12	144,292	157,877	147,662	163,985	210,169	242,400