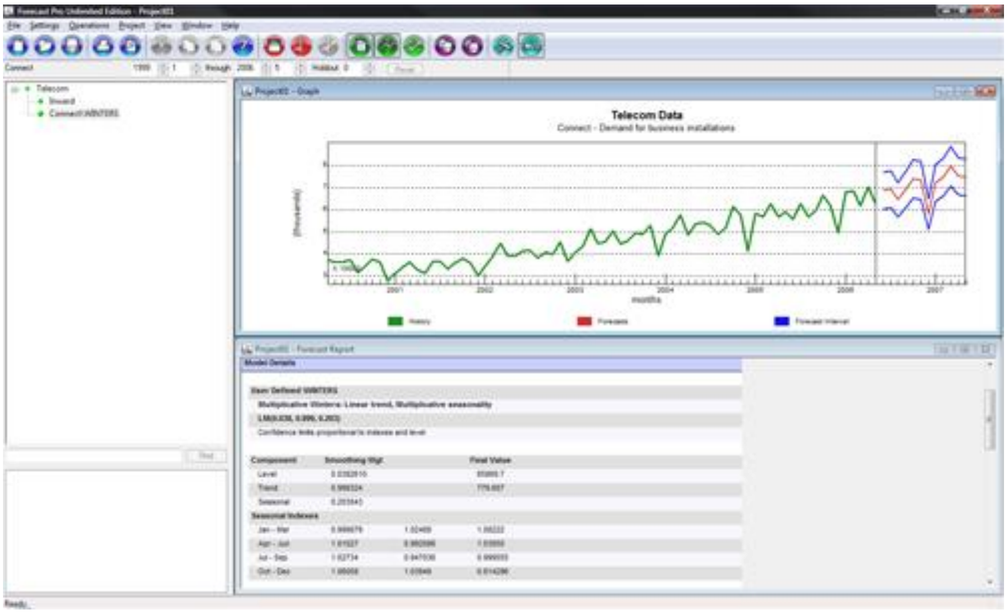
Forecasting 101: Exponential Smoothing Demystified
Part I - A Conceptual Overview

Exponential smoothing is the method of choice for many corporate forecasters. The technique creates accurate forecasts, is easy to apply and can be automated, which allows it to be used for large scale forecasting. In a series of three articles, *Forecasting 101* will examine how this important technique works, how to apply it and how to interpret the results. This first article provides a conceptual overview of exponential smoothing models and how they work.

Exponential smoothing is a *time series* forecasting technique. (Time series methods are forecasting techniques that base the forecast solely on the history of the item you are forecasting.) As a time series technique, exponential smoothing models are appropriate when you can assume a reasonable amount of continuity between the past and the future. The models are best suited to shorter-term forecasting—say 24 months or less—due to their assumption that future patterns and trends will resemble current patterns and trends. This is a reasonable assumption in the short term but becomes more tenuous the further out you forecast.

Exponential smoothing is not a single model but rather a family of models. The models estimate and forecast the level of the data along with different types of trends and seasonal patterns. The models are adaptive, and when generating the forecasts give greater emphasis to the recent history versus the more distant past.

A Component View of Data



The data above are both trended and seasonal. The lower portion of the screen displays the smoothing weights and final values from a Winters exponential smoothing model.

Exponential smoothing models assume that the time series has up to three underlying data components—level, trend and seasonality. The goal of the exponential smoothing model is to estimate the “final values” of the level, trend and seasonal pattern (i.e., their values at the end of the data). These final values are then used to construct the forecasts.

Each of the components is assumed to be changing in time. For example, the trend at the beginning of the data may be quite different than the trend at the end of the data. In addition, the data are assumed to contain random variation (noise) that has nothing to do with the underlying level, trend and seasonal pattern.

The Role of the Smoothing Weight
If we are trying to estimate the final value for a component and we know that it is changing in time, it makes sense to give greater emphasis to the most recent history versus the more distant past, due to the fact that the component is changing and therefore the recent history more accurately reflects current conditions. On the other hand, if we know that the data are noisy, it is beneficial to use a lot of data to estimate the component to cancel out the noise. So essentially we have a balancing act—we want to concentrate on the most recent data to capture change, but we want to go back further in time to smooth out the noise.

Exponential smoothing models use a series of smoothing weights to determine the amount of emphasis to give to each data point when estimating the final values of the components. The weights give the most emphasis to the most recent data and decrease exponentially as you go back in time.

The details about how the weights are estimated and applied, along with the smoothing equations that are used, are fully detailed in the *Forecast Pro Statistical Reference Manual* as well as virtually every textbook on statistical forecasting. *The Forecast Pro Statistical Reference Manual* is a pdf document that is copied to the program directory when you install Forecast Pro. It is also accessible via the Forecast Pro Help System and is the primary suggested reference for exponential smoothing models and all of the other forecasting techniques, statistics and algorithms found in Forecast Pro.

A Family of Models
There are many forms of exponential smoothing. Forecast Pro implements the *Holt-Winters* family of exponential smoothing models.

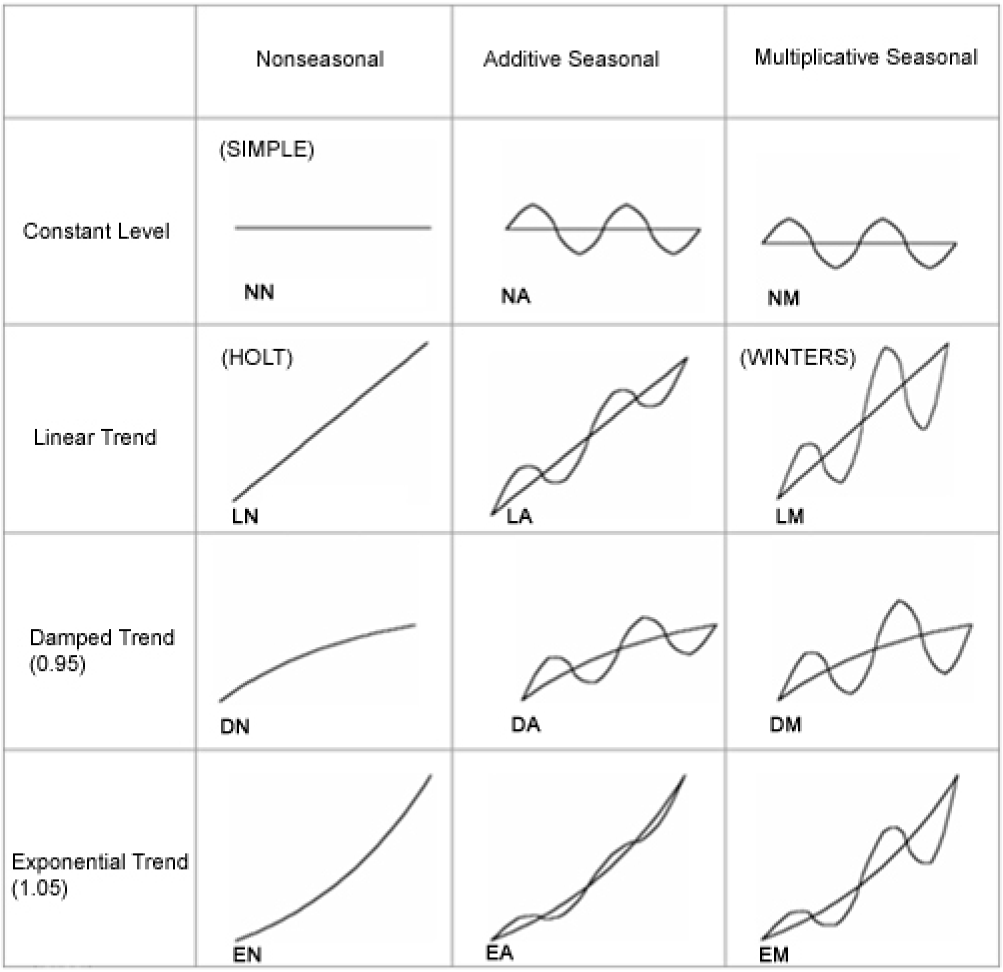


Figure 1

Forecast profiles from exponential smoothing adapted from E. Gardner, Journal of Forecasting, Vol. 4 (1985)

Figure 1 depicts forecast profiles generated from the twelve different exponential smoothing models that make up the Holt-Winters family. The models vary by how they forecast trends and seasonal patterns.

There are four options for forecasting the trend. The forecasts can be projected as nontrended (i.e., flat), or using a linear trend (i.e., a straight-line trend), or using a damped trend (i.e., a trend that dies out over time), or using an exponential trend (i.e., a trend which grows as a percentage of itself).

The seasonal models generate a set of indexes to model the seasonal contribution of each period during the year. For example if the data are monthly, 12 indexes are generated to capture the seasonal contribution of each month. The indexes are combined with the trend projection to create the forecasts.

There are three options for forecasting the seasonal pattern. The forecasts can be nonseasonal (i.e., indexes are not used), or projected using additive indexes (i.e., indexes that are added to the projected trend), or using multiplicative indexes (i.e., indexes that are multiplied into the projected trend). The difference between the additive and multiplicative index approaches is illustrated by the linear trend forecasts in Figure 1 above. In the additive seasonal approach, the amplitudes of the seasonal patterns remain constant, even as the underlying level increases. In the multiplicative seasonal approach the amplitudes increase as the level increases. In the general case, additive models generate constant seasonal variations regardless of the underlying trend and multiplicative models generate seasonal patterns that become more/less pronounced as the trend increases/decreases. Simply stated, multiplicative seasonal indexes introduce the seasonal variation as percentage adjustments to the underlying trend.

Coming Next: How to Select an Appropriate Model
In the next instalment of *Forecasting 101* we will explore both automatic and manual approaches to selecting an appropriate exponential smoothing model for a given data set.

About the author:
Eric Stellwagen is Vice President and co-founder of Business Forecast Systems, Inc. (BFS) and co-author of the Forecast Pro software product line. He consults widely in the area of practical business forecasting—spending 20-30 days a year presenting workshops on the subject—and frequently addresses professional groups such as the University of Tennessee's Sales Forecasting Management Forum, APICS and the Institute for Business Forecasting. Recognized as a leading expert in the field, he has worked with numerous firms including Coca-Cola, Procter & Gamble, Merck, Blue Cross Blue Shield, Nabisco, Owens-Corning and Verizon, and has served on the board of directors of the International Institute of Forecasters (IIF).