Predictive Planning Forecasting and Statistical Descriptions

The topics in this section are for those who want to know more about the forecasting methods and error measures used in Predictive Planning.

Classic Time-series Forecasting

Two primary techniques of classic time-series forecasting are used in Predictive Planning:

- Classic Nonseasonal Forecasting Methods — Estimate a trend by removing extreme data and reducing data randomness
- Classic Seasonal Forecasting Methods — Combine forecasting data with an adjustment for seasonal behavior

For information about autoregressive integrated moving average (ARIMA) time-series forecasting, see ARIMA Time-series Forecasting Methods.

Classic Nonseasonal Forecasting Methods

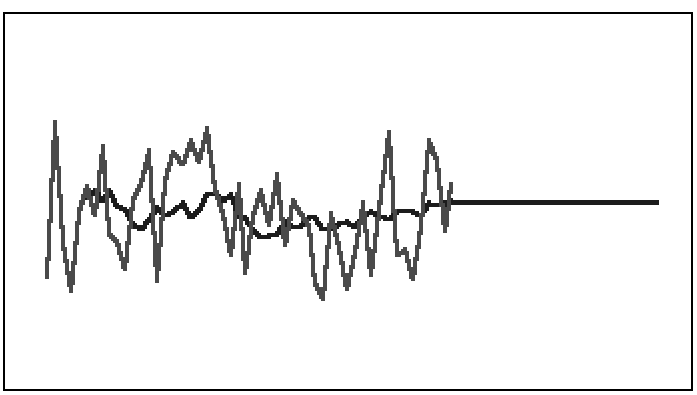
Nonseasonal methods attempt to forecast by removing extreme changes in past data where repeating cycles of data values are not present.

Single Moving Average (SMA)

Smooths historical data by averaging the last several periods and projecting the last average value forward.

This method is best for volatile data with no trend or seasonality. It results in a straight, flat-line forecast.

Figure B-1 Typical Single Moving Average Data, Fit, and Forecast Line

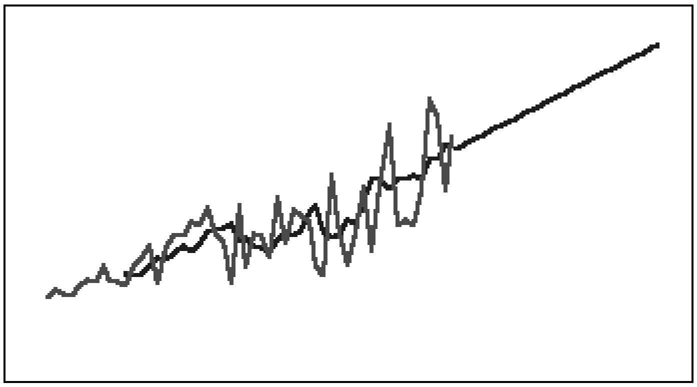


Double Moving Average (DMA)

Applies the moving average technique twice, once to the original data and then to the resulting single moving average data. This method then uses both sets of smoothed data to project forward.

This method is best for historical data with a trend but no seasonality. It results in a straight, sloped-line forecast.

Figure B-2   Typical Double Moving Average Data, Fit, and Forecast Line

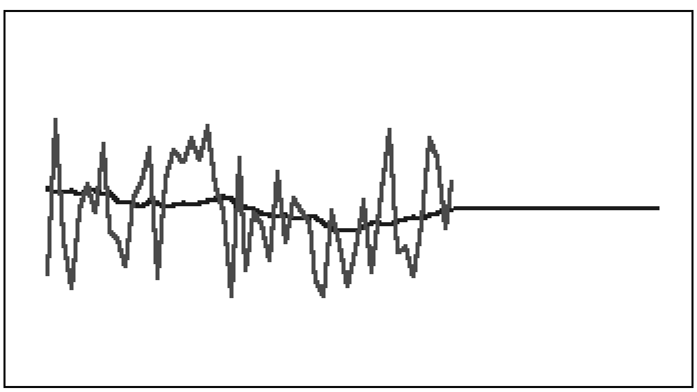


Single Exponential Smoothing (SES)

Weights all of the past data with exponentially decreasing weights going into the past. In other words, usually the more recent data has greater weight. Weighting in this way largely overcomes the limitations of moving averages or percentage change methods.

This method, which results in a straight, flat-line forecast is best for volatile data with no trend or seasonality.

Figure B-3   Typical Single Exponential Smoothing Data, Fit, and Forecast Line

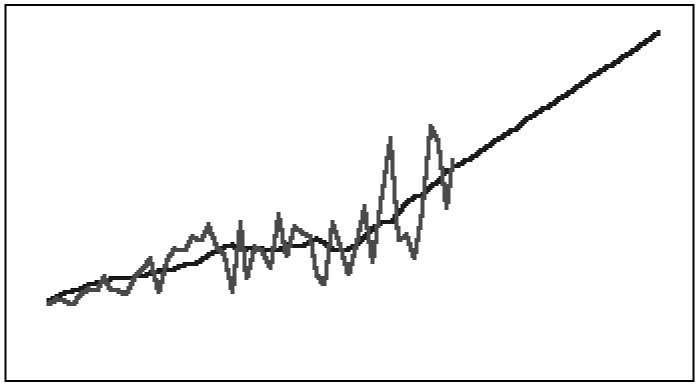


Double Exponential Smoothing (DES)

Applies SES twice, once to the original data and then to the resulting SES data. Predictive Planning uses Holt's method for double exponential smoothing, which can use a different parameter for the second application of the SES equation.

This method is best for data with a trend but no seasonality. It results in a straight, sloped-line forecast.

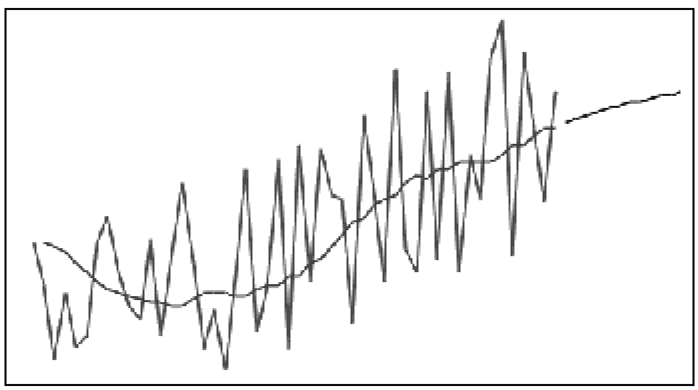
Figure B-4 Typical Double Exponential Smoothing Data, Fit, and Forecast Line



Damped Trend Smoothing (DTS) Nonseasonal Method

Applies exponential smoothing twice, similar to double exponential smoothing. However, the trend component curve is damped (flattens over time) instead of being linear. This method is best for data with a trend but no seasonality.

Figure B-5 Typical Damped Trend Smoothing Data, Fit, and Forecast Line



Classic Nonseasonal Forecasting Method Parameters

The classic nonseasonal methods use several forecasting parameters. For the moving average methods, the formulas use one parameter, period. When performing a moving average, Predictive Planning averages over a number of periods. For single moving average, the number of periods can be any whole number between 1 and half the number of data points. For double moving average, the number of periods can be any whole number between 2 and one-third the number of data points.

Single exponential smoothing has one parameter: alpha. Alpha (a) is the smoothing constant. The value of alpha can be any number between 0 and 1, not inclusive.

Double exponential smoothing has two parameters: alpha and beta. Alpha is the same smoothing constant as described above for single exponential smoothing. Beta (b) is also a smoothing constant exactly like alpha except that it is used during second smoothing. The value of beta can be any number between 0 and 1, not inclusive.

Damped trend smoothing has three parameters: alpha, beta, and phi (all between 0 and 1, not inclusive).

Classic Seasonal Forecasting Methods

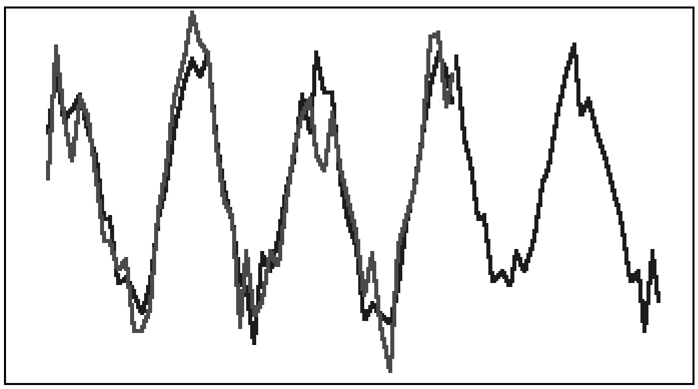
Seasonal forecasting methods extend the nonseasonal forecasting methods by adding an additional component to capture the seasonal behavior of the data.

Seasonal Additive

Calculates a seasonal index for historical data that does not have a trend. The method produces exponentially smoothed values for the level of the forecast and the seasonal adjustment to the forecast. The seasonal adjustment is added to the forecasted level, producing the seasonal additive forecast.

This method is best for data without trend but with seasonality that does not increase over time. It results in a curved forecast that reproduces the seasonal changes in the data.

Figure B-6 Typical Seasonal Additive Data, Fit, and Forecast Curve without Trend

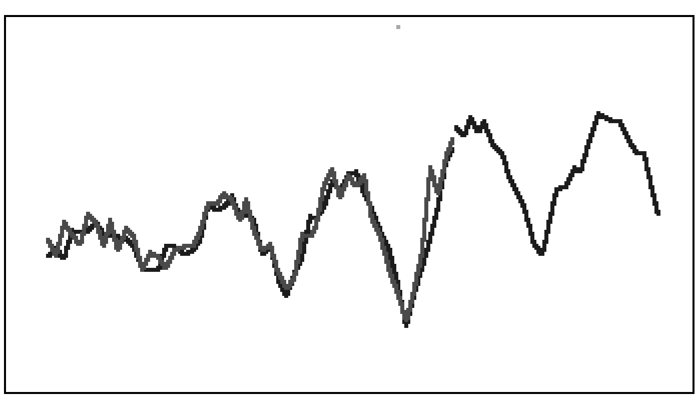


Seasonal Multiplicative

Calculates a seasonal index for historical data that does not have a trend. The method produces exponentially smoothed values for the level of the forecast and the seasonal adjustment to the forecast. The seasonal adjustment is multiplied by the forecasted level, producing the seasonal multiplicative forecast.

This method is best for data without trend but with seasonality that increases or decreases over time. It results in a curved forecast that reproduces the seasonal changes in the data.

Figure B-7 Typical Seasonal Multiplicative Data, Fit, and Forecast Curve without Trend

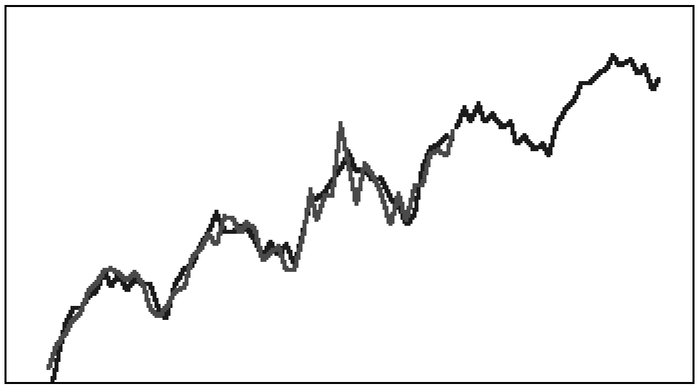


Holt-Winters' Additive

Is an extension of Holt's exponential smoothing that captures seasonality. This method produces exponentially smoothed values for the level of the forecast, the trend of the forecast, and the seasonal adjustment to the forecast. This seasonal additive method adds the seasonality factor to the trended forecast, producing the Holt-Winters' additive forecast.

This method is best for data with trend and seasonality that does not increase over time. It results in a curved forecast that shows the seasonal changes in the data.

Figure B-8 Typical Holt-Winters' Additive Data, Fit, and Forecast Curve

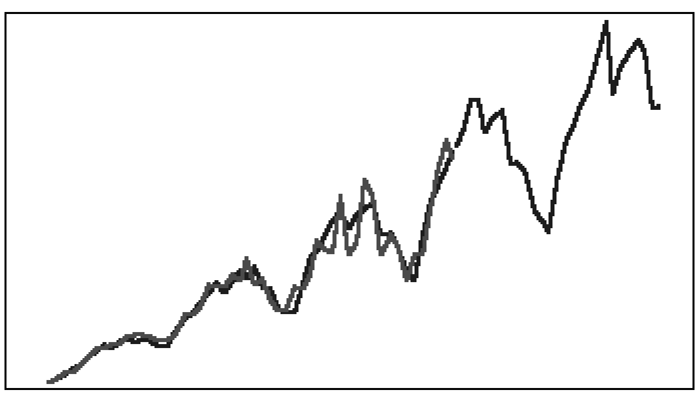


Holt-Winters' Multiplicative

Is similar to the Holt-Winters' additive method. Holt-Winters' Multiplicative method also calculates exponentially smoothed values for level, trend, and seasonal adjustment to the forecast. This seasonal multiplicative method multiplies the trended forecast by the seasonality, producing the Holt-Winters' multiplicative forecast.

This method is best for data with trend and with seasonality that increases over time. It results in a curved forecast that reproduces the seasonal changes in the data.

Figure B-9 Typical Holt-Winters' Multiplicative Data, Fit, and Forecast Curve

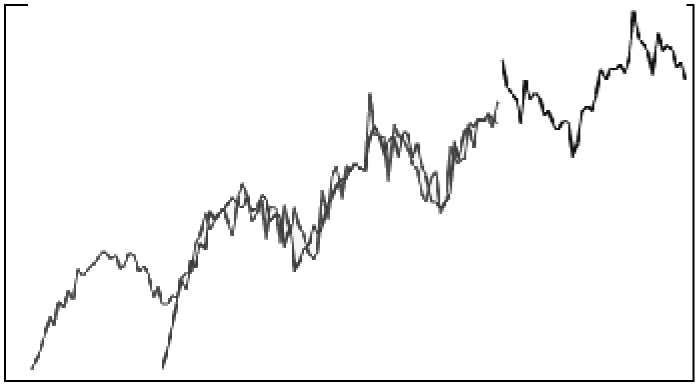


Damped Trend Additive Seasonal Method

Separates a data series into seasonality, damped trend, and level; projects each forward; and reassembles them into a forecast in an additive manner.

This method is best for data with a trend and with seasonality. It results in a curved forecast that flattens over time and reproduces the seasonal cycles.

Figure B-10 Typical Damped Trend Additive Data, Fit, and Forecast Curve

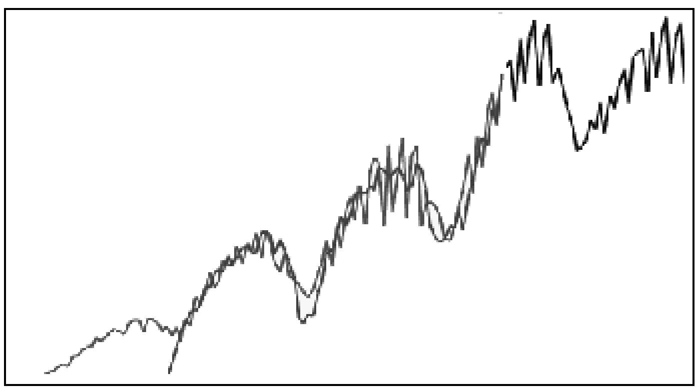


Damped Trend Multiplicative Seasonal Method

Separates a data series into seasonality, damped trend, and level; projects each forward; and reassembles them into a forecast in a multiplicative manner.

This method is best for data with a trend and with seasonality. It results in a curved forecast that flattens over time and reproduces the seasonal cycles.

Figure B-11 Typical Damped Trend Multiplicative Data, Fit, and Forecast Curve



Classic Seasonal Forecasting Method Parameters

The seasonal forecast methods use the following parameters:

- alpha (α) — Smoothing parameter for the level component of the forecast. The value of alpha can be any number between 0 and 1, not inclusive.
- beta (β) — Smoothing parameter for the trend component of the forecast. The value of beta can be any number between 0 and 1, not inclusive.
- gamma (γ) — Smoothing parameter for the seasonality component of the forecast. The value of gamma can be any number between 0 and 1, not inclusive.
- phi (Φ) — Damping parameter; any number between 0 and 1, not inclusive.

Each seasonal forecasting method uses some or all of these parameters, depending on the forecasting method. For example, the seasonal additive forecasting method does not account for trend, so it does not use the beta parameter.

The damped trend methods use phi in addition to the other three.

ARIMA Time-series Forecasting Methods

Autoregressive integrated moving average (ARIMA) forecasting methods were popularized by G. E. P. Box and G. M. Jenkins in the 1970s. These techniques, often called the Box-Jenkins forecasting methodology, have the following steps:

1. Model identification and selection
2. Estimation of autoregressive (AR), integration or differencing (I), and moving average (MA) parameters
3. Model checking

ARIMA is a univariate process. Current values of a data series are correlated with past values in the same series to produce the AR component, also known as *p*. Current values of a random error term are correlated with past values to produce the MA component, *q*. Mean and variance values of current and past data are assumed to be stationary, unchanged over time. If necessary, an I component (symbolized by *d*) is added to correct for a lack of stationarity through differencing.

In a nonseasonal ARIMA(*p*,*d*,*q*) model, *p* indicates the number or order of AR terms, *d* indicates the number or order of differences, and *q* indicates the number or order of MA terms. The *p*, *d*, and *q* parameters are integers equal to or greater than 0.

Cyclical or seasonal data values are indicated by a seasonal ARIMA model of the format:

SARIMA(*p*,*d*,*q*)(*P*,*D*,*Q*)(*t*)

The second group of parameters in parentheses are the seasonal values. Seasonal ARIMA models consider the number of time periods in a cycle. For a year, the number of time periods (*t*) is 12.

Note:

In Predictive Planning charts, tables, and reports, seasonal ARIMA models do not include the (*t*) component, although it is still used in calculations.

Predictive Planning ARIMA models do not fit to constant datasets or datasets that can be transformed to constant datasets by nonseasonal or seasonal differencing. Because of that feature, all constant series, or series with absolute regularity such as data representing a straight line or a saw-tooth plot, do not return an ARIMA model fit.

Time-series Forecasting Error Measures

One component of every time-series forecast is the data's random error that is not explained by the forecast formula or by the trend and seasonal patterns. The error is measured by fitting points for the time periods with historical data and then comparing the fitted points to the historical data.

RMSE

RMSE (root mean squared error) is an absolute error measure that squares the deviations to keep the positive and negative deviations from cancelling out one another. This measure also tends to exaggerate large errors, which can help eliminate methods with large errors.

Forecasting Method Selection

All of the nonseasonal forecasting methods and the ARIMA method are run against the data.

If the data is detected as being seasonal, the seasonal forecasting methods are run against the data.

The forecasting method with the lowest error measure (for example, RMSE) is used to forecast the data.