

In This Issue

1. Learn about the eight most common models used in time-series analysis
2. Perform a time-series analysis utilizing a sample from *Risk Simulator's* example folder

“How do you perform a time-series analysis using Risk Simulator?”

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Theory

The eight most common time-series models, segregated by seasonality and trend, are shown in Figure 1. For instance, if the data variable has no trend or seasonality, then a single moving-average model or a single exponential-smoothing model would suffice. However, if seasonality exists but no discernible trend is present, either a seasonal additive or seasonal multiplicative model would be better, etc.

	No Seasonality	With Seasonality
No Trend	Single Moving Average	Seasonal Additive
	Single Exponential Smoothing	Seasonal Multiplicative
With Trend	Double Moving Average	Holt-Winter's Additive
	Double Exponential Smoothing	Holt-Winter's Multiplicative

Figure 1. The Eight Most Common Time-Series Methods

Procedure

- Start Excel and type in or open an existing spreadsheet with the relevant historical data (the following example uses the *Time-Series Forecasting* file in the examples folder).
- Make sure you start a new simulation profile or that there is an existing profile in the model if you want the forecast results to automatically generate Monte Carlo assumptions.
- Select the historical data not including the variable name (data should be listed in a single column).
- Select *Risk Simulator | Forecasting | Time-Series Analysis* (see Figure 2).
- Choose the model to apply, enter the relevant assumptions, and click *OK*.

To follow along in this example, choose *Auto Model Selection*, enter 4 for seasonality periods per cycle, and forecast for 4 periods. Figure 3 shows the sample results generated by using the *Forecasting* tool. The model used was a Holt-Winters multiplicative model. Notice that in Figure 3, the model-fitting and forecast chart indicate that the trend and seasonality are picked up nicely by the Holt-Winters multiplicative model. The time-series analysis report provides the relevant optimized alpha, Beta, and gamma parameters; the error measurements; fitted data; forecast values; and forecast-fitted graph. The parameters are simply for reference. Alpha captures the memory effect of the base-level changes over time, Beta is the trend parameter that measures the strength of the trend, while gamma measures the seasonality strength of the historical data. The analysis decomposes the historical data into these three elements and then recomposes them to forecast the future. The fitted data illustrate the historical data and, using the recomposed model, show how close the forecasts are in the past (a technique called *backcasting*). The forecast values are either single-point estimates or assumptions (if the automatically generated assumptions option is chosen and if a simulation profile exists). The graph illustrates the historical, fitted, and forecast values. The chart is a powerful communication and visual tool to see how good the forecast model is.

This time-series analysis module contains the eight time-series models shown in Figure 1. You can choose the specific model to run based on the trend and seasonality criteria or choose the Auto Model Selection, which will automatically iterate through all eight methods, optimize the parameters, and find the best-fitting model for your data. Alternatively, if you choose one of the eight models, you can also deselect the Optimize checkboxes and enter your own alpha, Beta, and gamma parameters. In addition, you would need to enter the relevant seasonality periods if you choose the automatic model

selection or any of the seasonal models. The seasonality input must be a positive integer (e.g., if the data is quarterly, enter 4 as the number of seasons or cycles a year, or enter 12 if monthly data, or any other positive integer representing the data periods of a full cycle). Next, enter the number of periods to forecast. This value also has to be a positive integer. The maximum runtime is set at 300 seconds. Typically, no changes are required. However, when forecasting with a significant amount of historical data, the analysis might take slightly longer and if the processing time exceeds this runtime, the process will be terminated. You can also elect to have the forecast automatically generate assumptions; that is, instead of single-point estimates, the forecasts will be assumptions. However, to automatically generate assumptions, a simulation profile must first exist. Finally, the polar parameters option allows you to optimize the alpha, Beta, and gamma parameters to include zero and one. Certain forecasting software allows these polar parameters while others do not. Risk Simulator allows you to choose which to use. Typically, there is no need to use polar parameters.

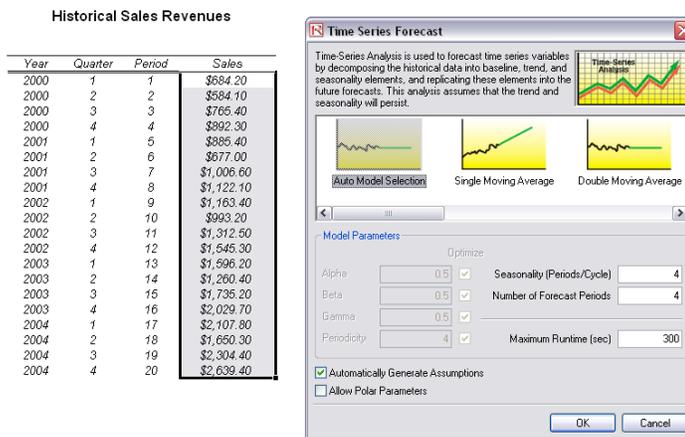


Figure 2. Time-Series Analysis

Holt-Winter's Multiplicative

Summary Statistics			
Alpha	Beta	Gamma	RMSE
0.00	0.00	0.00	914.824
0.10	0.10	0.10	415.322
0.20	0.20	0.20	187.202
0.30	0.30	0.30	118.795
0.40	0.40	0.40	101.794
0.50	0.50	0.50	102.143

The analysis was run with alpha = 0.2429, beta = 1.0000, gamma = 0.7797, and seasonality = 4

Time-Series Analysis Summary

When both seasonality and trend exist, more advanced models are required to decompose the data into their base elements: a base-case level (L) weighted by the alpha parameter; a trend component (b) weighted by the beta parameter; and a seasonality component (S) weighted by the gamma parameter. Several methods exist but the two most common are the Holt-Winter's additive seasonality and Holt-Winter's multiplicative seasonality methods. In the Holt-Winter's additive model, the base case level, seasonality, and trend are added together to obtain the forecast fit.

The best-fitting test for the moving average forecast uses the root mean squared errors (RMSE). The RMSE calculates the square root of the average squared deviations of the fitted values versus the actual data points.

Mean Squared Error (MSE) is an absolute error measure that squares the errors (the difference between the actual historical data and the forecast-fitted data predicted by the model) to keep the positive and negative errors from canceling each other out. This measure also tends to exaggerate large errors by weighting the large errors more heavily than smaller errors by squaring them, which can help when comparing different time-series models. Root Mean Square Error (RMSE) is the square root of MSE and is the most popular error measure, also known as the quadratic loss function. RMSE can be defined as the average of the absolute values of the forecast errors and is highly appropriate when the cost of the forecast errors is proportional to the absolute size of the forecast error. The RMSE is used as the selection criteria for the best-fitting time-series model.

Mean Absolute Percentage Error (MAPE) is a relative error statistic measured as an average percent error of the historical data points and is most appropriate when the cost of the forecast error is more closely related to the percentage error than the numerical size of the error. Finally, an associated measure is the Theil's U statistic, which measures the naivety of the model's forecast. That is, if the Theil's U statistic is less than 1.0, then the forecast method used provides an estimate that is statistically better than guessing.

Period	Actual	Forecast Fit	Error Measurements	
1	684.20		RMSE	71.8132
2	584.10		MSE	5157.1348
3	765.40		MAPE	53.4071
4	892.30		MAPE	4.50%
5	885.40	684.20	Theil's U	0.3054
6	677.00	667.55		
7	1006.60	935.45		
8	1122.10	1198.09		
9	1163.40	1112.48		
10	993.20	887.95		
11	1312.50	1348.38		
12	1545.30	1546.53		
13	1596.20	1572.44		
14	1260.40	1299.20		
15	1735.20	1704.77		
16	2029.70	1976.23		
17	2107.80	2026.01		
18	1650.30	1637.28		
19	2304.40	2245.93		
20	2639.40	2643.09		
Forecast 21		2713.69		
Forecast 22		2114.79		
Forecast 23		2900.42		
Forecast 24		3293.81		

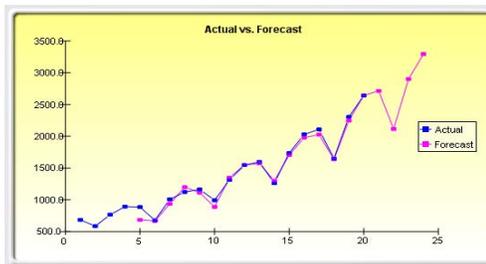


Figure 3. Example Holt-Winters Forecast Report