What’s New in SigmaXL® Version 9

Part 3 of 3: Control Charts for Autocorrelated Data

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Webinar December 10, 2020
Agenda

• Introduction
• Autocorrelation
• Example 1: Chemical Process Concentration
• Simple Exponential Smoothing (EWMA)
• Example 2: Ln(Monthly Airline Passengers-Modified)
Agenda

• Error, Trend, Seasonal (ETS) Exponential Smoothing models

• Autoregressive Integrated Moving Average (ARIMA) models

• ARIMA with Predictors
  — Analyze control chart outlier versus shift
  — Example 3: Electricity Demand with Temperature and Work Day Predictors

• Questions/References
Introduction

• Statistical process control for autocorrelated processes typically use the EWMA (Exponentially Weighted Moving Average) one-step-ahead forecast model.

• The time series model forecasts the motion in the mean and an Individuals control chart is plotted of the residuals to detect assignable causes.
Introduction

• Failure to account for the autocorrelation will produce limits that are too narrow resulting in excessive false alarms, or limits that are too wide resulting in misses.

• The challenge with this approach is that if there is seasonality or negative autocorrelation in the data, the user needs an advanced level of knowledge in forecasting methods to pick the correct model, e.g., Seasonal Exponential Smoothing models or Seasonal Autoregressive Integrated Moving Average (ARIMA) models are required.
Introduction

• We will review simple exponential smoothing/EWMA, then introduce recent developments in time series forecasting that use automatic model selection to accurately pick the time series model that produces a minimum forecast error.

• An accurate forecast for your time series means the residuals will most often have the right properties to correctly apply a control chart, thus leading to an improved control chart with reduced false alarms and misses.
Autocorrelation

• Just as correlation measures the extent of a linear relationship between two variables, autocorrelation (AC) measures the linear relationship between lagged values of data.

• A plot of the data vs. the same data at lag $k$ will show a positive or negative trend. If the slope is positive, the AC is positive; if there is a negative slope, the AC is negative.

• The Autocorrelation Function (ACF) formula is:

$$r_k = \frac{\sum_{t=k+1}^{T} (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T} (y_t - \bar{y})^2}$$

where $T$ is length of the time series [4].
Autocorrelation

Any statistically significant correlation \((r_k > 2/\sqrt{N})\) will adversely affect the performance of a Shewhart control chart.

The Ljung-Box test is used to determine if a group of autocorrelations are significant (see formula in Appendix).
Example 1: Box-Jenkins Series A - Chemical Process Concentration - Autocorrelation Function (ACF) Plot

SigmaXL > Time Series Forecasting > Autocorrelation (ACF/PACF) Plots
Example 1: Chemical Process Concentration - Series A.xlsx - Concentration
Example 1: Box-Jenkins Series A - Chemical Process Concentration - Run Chart
Example 1: Box-Jenkins Series A - Chemical Process
Concentration - Individuals Control Chart

17 out-of-control data points

SigmaXL > Control Charts > Individuals
Autocorrelation

Guidelines from Woodall & Faltin [10]:

• If possible, one should first attempt to remove the source of the autocorrelation.

• If the source of autocorrelation cannot be removed directly, then it may be possible to model the autocorrelation and use a feedback control scheme to reduce variability about a specified target value.

• If the source of the autocorrelation cannot be removed directly, and feedback control is not a viable option, then it is important to monitor the process with control charts which do not repeatedly give signals due to presence of the autocorrelation.
Simple (Single) Exponential Smoothing
Exponentially Weighted Moving Average (EWMA)

Forecasts are calculated using weighted averages, where the weights decrease exponentially as observations come from further in the past with the smallest weights associated with the oldest observations:

\[ \hat{y}_{t+1} = \alpha \ y_t + \alpha (1 - \alpha) \ y_{t-1} + \alpha (1 - \alpha)^2 \ y_{t-2} + \cdots \]

where \( 0 \leq \alpha \leq 1 \) is the level smoothing parameter [4].
Simple (Single) Exponential Smoothing
Exponentially Weighted Moving Average (EWMA)

Weights for Different Alpha Values

- Alpha=0.2
- Alpha=0.4
- Alpha=0.6
- Alpha=0.8

Weights: t-5, t-4, t-3, t-2, t-1, t
Simple (Single) Exponential Smoothing
Exponentially Weighted Moving Average (EWMA)

• An equivalent formulation for simple exponential smoothing is:

\[ \hat{y}_{t+1} = \alpha \hat{y}_t + (1 - \alpha) y_t \]

with the starting forecast value (initial level) \( \hat{y}_1 \) typically estimated as \( y_1 \).

• The formula used for EWMA is the same, but the smoothing parameter \( \lambda \) is typically used instead of \( \alpha \) and \( X_t \) instead of \( y_t \):

\[ \text{EWMA}_{t+1} = \lambda X_t + (1 - \lambda) \text{EWMA}_t \]

with the starting forecast value \( \text{EWMA}_1 \) estimated as the data mean or target value.
Simple (Single) Exponential Smoothing
Exponentially Weighted Moving Average (EWMA)

• In the case of an EWMA control chart, the smoothing parameter $\lambda$ is determined by desired average run length characteristics and is typically 0.2.

• For forecasting or SPC for autocorrelated data, the smoothing parameter and initial level are determined by minimizing the sum-of-square forecast errors (residuals):

$$SSE = \sum_{t=1}^{T} (y_t - \hat{y}_t)^2 = \sum_{t=1}^{T} e_t^2.$$  

• This involves non-linear minimization methods like Newton-Raphson or Nelder-Mead Simplex.
Simple (Single) Exponential Smoothing
Exponentially Weighted Moving Average (EWMA)

- As usual for any statistical model, the residuals should be normal, independent and identically distributed.
- If this is achieved, this also means that the assumptions for a Shewhart control chart are satisfied.
Example 1: Box-Jenkins Series A - Chemical Process Concentration - Simple Exponential Smoothing (EWMA) Time Series Forecast

SigmaXL > Time Series Forecasting > Exponential Smoothing Forecast > Forecast
Example 1: Box-Jenkins Series A - Chemical Process Concentration - Simple Exponential Smoothing (EWMA)

Exponential Smoothing Time Series Forecast Chart
95.0% Prediction Intervals

Exponential Smoothing Model: Concentration
Model Type: Simple Exponential Smoothing with Additive Errors (A, N, N) - Exponentially Weighted Moving Average (EWMA)
Model Periods: All observations are used in the Exponential Smoothing model estimation. No withhold periods available for out-of-sample forecast accuracy evaluation.

Exponential Smoothing Model Information
- Seasonal Frequency: 1
- Model selection criterion: AICc
- Box-Cox Transformation: N/A
- Lambda
- Threshold

Parameter Estimates
- Term: alpha (level smoothing)
- Coefficient: 0.294785988
- I (level initial state): 16.73121246

Exponential Smoothing Model Statistics
- No. Observations: 197
- DF: 194
- StDev: 0.319007644
- Variance: 0.101765877
- Log-Likelihood: -293.8036067
- AICc: 593.7315658
- AIC: 593.6072135
- BIC: 603.4568246

Forecast Accuracy
- Metric: N
- In-Sample (Estimation) One-Step-Ahead Forecast: N
- Out-of-Sample (Withhold) One-Step-Ahead Forecast: N
- Out-of-Sample (Withhold) Full Period Forecast: N
- RMSE: 0.316569334
- MAE: 0.247329038
- MAPE: 1.446520183
- MASE: 0.897712804

Simple Exponential Smoothing (EWMA) specified. 95% Prediction Intervals for forecast.
Example 1: Box-Jenkins Series A - Chemical Process Concentration - ACF Plots (Raw Data versus Residuals)
Example 1: Box-Jenkins Series A - Chemical Process
Concentration - Residuals

Residuals look good – approximately normal with equal variance.
Example 1: Box-Jenkins Series A - Chemical Process Concentration - Simple Exponential Smoothing (EWMA) Control Chart

SigmaXL > Time Series Forecasting > Exponential Smoothing Control Chart > Control Chart
Example 1: Box-Jenkins Series A - Chemical Process Conc. -

Individuals Control Chart (Raw Data versus Residuals)

Originally 17 out-of-control data points. Many are false alarms due to autocorrelation.

Now only 2 out-of-control data points. These should be investigated.

SigmaXL > Time Series Forecasting > Exponential Smoothing Control Chart > Control Chart
Example 1: Box-Jenkins Series A - Chemical Process Concentration – Moving Limits Control Chart

The Moving Limits chart uses the one step prediction as the center line, so the control limits will move with the center line.

SigmaXL > Time Series Forecasting > Exponential Smoothing Control Chart > Control Chart
Example 1: Box-Jenkins Series A - Chemical Process
Concentration - Individuals Control Chart: Enable Scrolling

SigmaXL Chart Tools > Enable Scrolling
Now we will add a new data point to the Series A Concentration Data. The residuals will be computed using the same model as above without re-estimation of the model parameters or recalculation of the control limits. This is also known as the “Phase II” application of a Control Chart, where an out-of-control signal should lead to an investigation into the assignable cause and corrective action or process adjustment applied.
Example 1: Box-Jenkins Series A - Chemical Process
Concentration - Individuals Control Chart: Add Data

SigmaXL Chart Tools > Add Data to this Control Chart
Example 2a: Box-Jenkins Series G – Ln(Monthly Airline Passengers) - Run Chart

Data modified with negative outlier at 50 (-.25) and level shift (+.25) starting at 100.

Data shows strong positive trend and strong seasonality (monthly data).

SigmaXL > Time Series Forecasting > Run Chart
Example 2: Airline Passengers Modified.xlsx – Ln(Airline Passengers)
Example 2a: Box-Jenkins Series G – Ln(Monthly Airline Passengers) - Individuals Control Chart

The control chart signals here are meaningless.

SigmaXL > Control Charts > Individuals
Example 2a: Box-Jenkins Series G – Ln(Monthly Airline Passengers) - Autocorrelation (ACF) Plot

SigmaXL > Time Series Forecasting > Autocorrelation (ACF/PACF) Plots
Error, Trend, Seasonal (ETS) Exponential Smoothing Models

• Error, Trend, Seasonal (ETS) models expand on simple exponential smoothing to accommodate trend and seasonal components as well as additive or multiplicative errors.

• Simple Exponential Smoothing is an Error Model.

• Error, Trend model is Holt’s Linear, also known as double exponential smoothing.
Error, Trend, Seasonal (ETS) Exponential Smoothing Models

• Error, Trend, Seasonal model is Holt-Winters, also known as triple exponential smoothing.
  
  − Seasonal frequency must be specified:
    • Quarterly data = 4 (observations per year)
    • Monthly data = 12 (observations per year)
    • Daily data = 7 (observations per week)
    • Hourly data = 24 (observations per day)
  
  − Frequency is the number of observations per “cycle”. This is the opposite of the definition of frequency in physics, or in engineering Fourier analysis, where “period” is the length of the cycle, and “frequency” is the inverse of period.

Reference: https://robjhyndman.com/hyndsight/seasonal-periods/
Error, Trend, Seasonal (ETS) models
Hyndman’s Taxonomy

SigmaXL > Time Series Forecasting > Exponential Smoothing Forecast > Forecast
Example 2b: Box-Jenkins Series G – Ln(Monthly Airline Passengers) – Exponential Smoothing Forecast with Automatic Model Selection

SigmaXL > Time Series Forecasting > Exponential Smoothing Forecast > Forecast
Example 2b: Box-Jenkins Series G – Ln(Monthly Airline Passengers) Seasonal Exponential Smoothing with Trend


SigmaXL > Time Series Forecasting > Exponential Smoothing Forecast > Forecast
Example 2b: Box-Jenkins Series G – Ln(Monthly Airline Passengers) - ACF Plots (Raw Data versus Residuals)
Example 2b: Box-Jenkins Series G – Ln(Monthly Airline Passengers) – Exponential Smoothing Control Chart with Automatic Model Selection

SigmaXL > Time Series Forecasting > Exponential Smoothing Control Chart > Control Chart
Example 2b: Box-Jenkins Series G – Ln(Monthly Airline Passengers) Exponential Smoothing Control Charts

Assignable causes at points 50 and 100 are detected.

Exponential Smoothing Residuals Individuals Chart

Exponential Smoothing Moving Limits Chart

Exponential Smoothing Model: Additive Trend, Additive Seasonal Method with Additive Errors (Holt-Winters) (A, A, A) - Model Automatically Selected
Model Periods: All observations are used in the Exponential Smoothing model estimation. No withhold periods available for out-of-sample forecast accuracy evaluation.
Example 2b: Box-Jenkins Series G – Ln(Monthly Airline Passengers) - Individuals Control Chart for Raw Data

The control chart signals here are meaningless.

SigmaXL > Control Charts > Individuals
Box-Jenkins AutoRegressive Integrated Moving Average (ARIMA) Models

• An ARIMA model includes an Autoregressive (AR) component of order $p$, an Integrated/Differencing component of order $d$ and a Moving Average component of order $q$ and an optional constant.

• An ARIMA Seasonal model includes a Seasonal Autoregressive (SAR) component of order $P$, a Seasonal Integrated/Differencing component of order $D$ and a Seasonal Moving Average component of order $Q$. 
Box-Jenkins AutoRegressive Integrated Moving Average (ARIMA) Models

SigmaXL > Time Series Forecasting > ARIMA Forecast > Forecast
Example 2c: Box-Jenkins Series G – Ln(Monthly Airline Passengers) – ARIMA Forecast with Automatic Model Selection

SigmaXL > Time Series Forecasting > ARIMA Forecast > Forecast
Example 2c: Box-Jenkins Series G – Ln(Monthly Airline Passengers)

ARIMA (0,1,1) (0,1,1) automatically selected. Seasonal Frequency = 12 (Monthly data).

SigmaXL > Time Series Forecasting > ARIMA Forecast > Forecast

ARIMA Model: Ln (Airline Passengers)

Model Periods: All observations are used in the ARIMA model estimation. No withhold periods available for out-of-sample forecast accuracy evaluation.

<table>
<thead>
<tr>
<th>ARIMA Model Summary</th>
<th>Parameter Estimates</th>
<th>ARIMA Model Statistics</th>
<th>Forecast Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR Order (p)</td>
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<td>Term</td>
<td>Coefficient</td>
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<td></td>
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<tr>
<td>Lambda</td>
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</table>

| No. Observations | 144 | DF | 129 | Variance | 0.002959687 |
| Log-Likelihood | 191.5831814 | AICc | -376.9773864 | MAE | 0.036285476 |
| AIC | -377.1663627 | MAPE | 0.648152199 | MASE | 0.249152876 |
| BIC | -368.5407708 | | | | | |

95.0% Prediction Intervals
Example 2c: Box-Jenkins Series G – Ln(Monthly Airline Passengers)

Autocorrelation Function (ACF) Plot
Significance Limit Alpha = 0.05

Partial Autocorrelation Function (PACF) Plot
Significance Limit Alpha = 0.05

Autocorrelation Function (ACF) Plot - Residuals
Significance Limit Alpha = 0.05

Partial Autocorrelation Function (PACF) Plot - Residuals
Significance Limit Alpha = 0.05
Example 2c: Box-Jenkins Series G – Ln(Monthly Airline Passengers) – ARIMA Control Chart with Automatic Model Selection

SigmaXL > Time Series Forecasting > ARIMA Control Chart > Control Chart
Example 2c: Box-Jenkins Series G – Ln(Monthly Airline Passengers) ARIMA Control Charts

Points 1 to 13 are missing due to differencing.

Assignable causes at points 50 and 100 are detected.

ARIMA Model: Ln (Airline Passengers Modified) - Model Automatically Selected
Model Periods: All observations are used in the ARIMA model estimation. No withhold periods available for out-of-sample forecast accuracy evaluation.
ARIMA with Predictors

• The ARIMA model supports continuous or categorical predictors, similar to multiple regression.

• In order to provide a forecast, additional predictor (X) values must be added to the dataset prior to running the analysis. The number of forecast periods will be equal to the number of additional predictor rows. Alternatively, the predictor values from a withhold sample may be used.

• As with multiple linear regression, predictors should not be strongly correlated.
Example 2d: Box-Jenkins Series G – Ln(Monthly Airline Passengers) – Outlier versus Shift Coded Predictors

<table>
<thead>
<tr>
<th>Obs. No.</th>
<th>Ln (Airline Passengers-Modified)</th>
<th>Outlier 50</th>
<th>Shift 50</th>
<th>Outlier 100</th>
<th>Shift 100</th>
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<tbody>
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<td>1</td>
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</tbody>
</table>
Example 2d: Box-Jenkins Series G – Ln(Monthly Airline Passengers) – ARIMA Forecast with Predictors: Outlier versus Shift Coded Predictors

SigmaXL > Time Series Forecasting > ARIMA Forecast > Forecast with Predictors
Example 2d: Box-Jenkins Series G – Ln(Monthly Airline Passengers) – Outlier versus Shift Coded Predictors

Using ARIMA Forecast with Predictors, we can see that Outlier50 and Shift100 are significant denoting Obs. No. 50 as an outlier and 100 as a shift. This is, of course, what we expected since that’s how the Ln Airline Passenger data was modified.

This method to identify outlier versus shift is intended as a complement to process knowledge and the search for assignable causes used in classical SPC.

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
<th>SE Coefficient</th>
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SigmaXL > Time Series Forecasting > ARIMA Forecast > Forecast with Predictors
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – Run Chart

SigmaXL > Time Series Forecasting > Run Chart
Example 3: Daily Electricity Demand with Predictors – ElecDaily.xlsx
Victoria, Australia, 2014.
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors - Individuals Control Chart

SigmaXL > Control Charts > Individuals
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – Autocorrelation (ACF) Plot

SigmaXL > Time Series Forecasting > Autocorrelation (ACF/PACF) Plots
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors - Spectral Density Plot

SigmaXL > Time Series Forecasting > Spectral Density Plot
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors - Seasonal Trend Decomposition

SigmaXL > Time Series Forecasting > Seasonal Trend Decomposition Plots
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – Run Charts

SigmaXL > Time Series Forecasting > Run Chart

Example 3: Daily Electricity Demand with Predictors – ElecDaily.xlsx
Victoria, Australia, 2014.
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – Scatterplot and Box Plot

SigmaXL > Graphical Tools > Scatterplots
SigmaXL > Graphical Tools > Boxplots

Example 3: Daily Electricity Demand with Predictors – ElecDaily.xlsx
Victoria, Australia, 2014.
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – ARIMA Forecast with Predictors

SigmaXL > Time Series Forecasting > ARIMA Forecast > Forecast with Predictors

Example 3: Daily Electricity Demand with Predictors – ElecDaily.xlsx, Sheet “Forecast 2 Weeks”.
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – ARIMA Forecast with Predictors

ARIMA Model Summary

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
<th>SE Coefficient</th>
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</tbody>
</table>
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – ARIMA Forecast with Predictors
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – ARIMA Control Chart with Predictors

SigmaXL > Time Series Forecasting > ARIMA Control Chart > Control Chart with Predictors

Example 3: Daily Electricity Demand with Temperature and Work Day Predictors – ARIMA Control Chart with Predictors

ARIMA Residuals Individuals Chart

ARIMA Moving Limits Control Chart

ARIMA Model: Demand - Model Automatically Selected
Model Periods: All observations are used in the ARIMA model estimation. No withhold periods available for out-of-sample forecast accuracy evaluation.
Example 3: Daily Electricity Demand with Temperature and Work Day Predictors - Individuals Control Chart for Raw Data

Note the additional out-of-control signals.

SigmaXL > Control Charts > Individuals
What’s New in SigmaXL® Version 9

Part 3 of 3: Control Charts for Autocorrelated Data

Questions?
References


References


