Forecasting Workshop
Background

What it is: A detailed presentation focusing on the Mathematical methods of prediction that are standard in APO-Demand Planning.

It is based on the Functionality found in release 3.1.

Anyone interested in upgrading it to 4.0?
Overview of the Forecasting Workshop

1. Overview of Forecasting in APO
2. History
3. Univariate Forecast Basics
4. Univariate Models in APO
5. Forecast Error Analysis
6. Master Forecast Profile Setup
7. Forecast Execution
What we will talk about today

3. Univariate Forecast Basics
4. Univariate Models in APO
5. Forecast Error Analysis
Univariate Forecast Basics

Univariate Models in APO

Forecast Error Analysis
Elements of the Univariate Forecast

- Actual Value
- Basic Value
- Trend Value
- Seasonal Index
- Length of Season
- Initialization
- Ex-post Forecast
- Forecast
- Parameters

 Exceptions are models 13, 14, 35, 70, 80, 94
Historical values used as the basis of the forecast
Basic Value - Controls Vertical Placement

Data Values

Forecast Horizon

Basic Value

2000

1000

1

2
Trend - Slope of line

1

-0.75

2

0.75

Data Values

Forecast Horizon
Seasonal Index

Data Values

Forecast Horizon

Seasonal index - Divergence from Basic Value

1.00

2.50

0.25
Length of Season

Number of Periods in the Season
Typically = one year
Basic value, Trend value, Seasonal indices, and the Mean Absolute Deviation are initialized.

<table>
<thead>
<tr>
<th>Model</th>
<th>Fixed number of historical values used for initialization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1</td>
</tr>
<tr>
<td>Trend</td>
<td>3</td>
</tr>
<tr>
<td>Seasonal</td>
<td>1 season</td>
</tr>
<tr>
<td>Seasonal trend</td>
<td>3 + 1 season</td>
</tr>
<tr>
<td>2nd-order exponential smoothing</td>
<td>3</td>
</tr>
</tbody>
</table>
An Ex post Forecast is a forecast run in the past for comparison against historical values. The ex-post forecast is used to measure model fit.

- Initialization length is dependent on the forecast model
- Ex-post forecast length is the history horizon less the initialization horizon
The following Models do not generate an Ex-post forecast:

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>Moving average</td>
</tr>
<tr>
<td>14</td>
<td>Weighted moving average</td>
</tr>
<tr>
<td>60</td>
<td>Historical data adopted</td>
</tr>
<tr>
<td>70</td>
<td>Manual forecast</td>
</tr>
</tbody>
</table>
General Calculation

Basic\(t\), trend\(t\), seasonal\(t\)

\[=\]

Function(actual\(t\), basic\(t-1\), trend\(t-1\), seasonal\(t-1s\))

Forecast = Function(basic\(t\), trend\(t\), seasonal\(t\))
### Trend Model Example – Initialization & Ex-Post

<table>
<thead>
<tr>
<th>Period</th>
<th>History Horizon</th>
<th>Forecast Horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>History</td>
<td>80</td>
<td>95</td>
</tr>
<tr>
<td>G - Basic Value</td>
<td>102</td>
<td></td>
</tr>
<tr>
<td>T - Trend</td>
<td>10.0</td>
<td></td>
</tr>
<tr>
<td>EX Ex-post</td>
<td>112</td>
<td></td>
</tr>
<tr>
<td>F Forecast</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Trend Initialization

\[
\text{Trend Initialization} = \frac{\text{Hist}(3) - \text{Hist}(1)}{2}
\]

### Basic Value Initialization

\[
\text{Basic Value Initialization} = \frac{\text{Hist}(3) + \text{Hist}(2) + \text{Hist}(1)}{3} + \text{Trend}
\]

### Ex-Post Forecast

\[
\text{Ex}(t + i) = \text{G}(t) + i \times \text{T}(t)
\]

Where \( i = 1 \)
### Trend Model Example – Calculate New Basic and Trend

<table>
<thead>
<tr>
<th></th>
<th>History Horizon</th>
<th>Forecast Horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Period</strong></td>
<td>1  2  3  4  5  6  7</td>
<td>1  2  3  4</td>
</tr>
<tr>
<td><strong>History</strong></td>
<td>80  95  100  115  125  110  110</td>
<td></td>
</tr>
<tr>
<td><strong>G - Basic Value</strong></td>
<td>102</td>
<td>113</td>
</tr>
<tr>
<td><strong>T - Trend</strong></td>
<td><strong>10.0</strong></td>
<td><strong>10.3</strong></td>
</tr>
<tr>
<td><strong>EX - Ex-post</strong></td>
<td>112</td>
<td>123</td>
</tr>
<tr>
<td><strong>F Forecast</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Basic Value

\[
G(t) = \alpha V(t) + (1 - \alpha) \left[ G(t-1) + T(t-1) \right]
\]

\[
113 = 0.3 \times (115) + 0.7 \times [102 + 10.0]
\]

#### Trend Value

\[
T(t) = \beta \left[ G(t) - G(t-1) \right] + (1-\beta)T(t-1)
\]

\[
10.3 = 0.3 \times [113 - 102] + 0.7 \times 10.0
\]

#### Ex-Post Forecast

\[
Ex(t +i) = G(t) + i \times T(t)
\]

Where \(i = 1\)

\[
123 = 113 + 10.3
\]
### Trend Model Example – Calculation Repeated

<table>
<thead>
<tr>
<th>Period</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>History</td>
<td>80</td>
<td>95</td>
<td>100</td>
<td>115</td>
<td>125</td>
<td>110</td>
<td>110</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G - Basic Value</td>
<td>102</td>
<td>113</td>
<td>124</td>
<td>127</td>
<td>128</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T - Trend</td>
<td>10.0</td>
<td>10.3</td>
<td>10.5</td>
<td>8.3</td>
<td>6.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EX - Ex-post</td>
<td></td>
<td>112</td>
<td>123</td>
<td>134</td>
<td>135</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F Forecast</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>134</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Ex-Post Forecast**

\[
\text{Ex}(t + i) = G(t) + i \times T(t)
\]

Where \( i = 1 \)

**Forecast**

\[
\text{P}(t+i) = G(t) + i \times T(t)
\]

**Basic Value**

\[
G(t) = \alpha V(t) + (1 - \alpha) \left[ G(t-1) + T(t-1) \right]
\]

**Trend Value**

\[
T(t) = \beta \left[ G(t) - G(t-1) \right] + (1 - \beta)T(t-1)
\]
### Trend Model Example – Calculation Repeated

<table>
<thead>
<tr>
<th>Period</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
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<tr>
<td>History</td>
<td>80</td>
<td>95</td>
<td>100</td>
<td>115</td>
<td>125</td>
<td>110</td>
<td>110</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td>G - Basic Value</td>
<td>102</td>
<td>113</td>
<td>124</td>
<td>127</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td>T - Trend</td>
<td>10.0</td>
<td>10.3</td>
<td>10.5</td>
<td>8.3</td>
<td>6.1</td>
<td>6.1</td>
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<td>6.1</td>
</tr>
<tr>
<td>EX Ex-post</td>
<td>112</td>
<td>123</td>
<td>134</td>
<td>135</td>
<td>134</td>
<td>140</td>
<td>146</td>
<td>152</td>
<td>152</td>
<td>152</td>
<td>152</td>
</tr>
<tr>
<td>F Forecast</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Ex-Post Forecast

$$\text{Ex}(t+i) = G(t) + i \times T(t)$$

Where $i = 1$

#### Forecast

$$P(t+i) = G(t) + i \times T(t)$$

#### Basic Value

$$G(t) = \alpha V(t) + (1-\alpha) \left[ G(t-1) + T(t-1) \right]$$

#### Trend Value

$$T(t) = \beta \left[ G(t) - G(t-1) \right] + (1-\beta) T(t-1)$$
The model parameters, Alpha, Beta, and Gamma, control the weighting of each historical values.

- **Alpha** is used in the basic value calculation
- **Beta** is used in trend value calculation
- **Gamma** is used in the Seasonal index calculation

The value for the parameters range from 0 to 1. A higher value will place more emphasis on recent history.

The parameters also control how reactive the forecast is to changes in historical patterns.
Univariate Forecast Basics

Univariate Models in APO

Forecast Error Analysis
Univariate Forecasting Models

- Constant Models
- Moving Average Models
- Trend Models
- Seasonal Models
- Seasonal Trend Models
- Automatic Model Selection I and II
- Sporadic Demand
- Historical Data Model
- Linear Regression
- User Exit
Constant Models

3 models within the constant model group:

- Constant Model (10)
- 1st Order Exponential Smoothing (11)
- Constant Model with automatic Alpha adaptation (12)

Constant Models follow the pattern:

\[
10 = 11
\]

Same Formula!
Constant Model – 1st order Exponential Smoothing (10,11)

Use this model when there are no seasonal variations or trend patterns. Alpha parameter controls the weighting of history in determining the basic value.

\[
G(t) = \alpha V(t) + (1 - \alpha) G(t-1)
\]

- Basic value and ex-post forecast are equal
- Higher alpha puts more weight on recent values
- Higher alpha makes the forecast more reactive to recent changes in history
Example of a Constant Model

<table>
<thead>
<tr>
<th>Date</th>
<th>Statistical Forecast</th>
<th>Adjusted Sales History</th>
<th>Corrected History</th>
<th>Ex-post Forecast</th>
<th>Corrected Forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td>M 08.2003</td>
<td>6888</td>
<td>6893</td>
<td>6689</td>
<td>7001</td>
<td>6804</td>
</tr>
<tr>
<td>M 09.2003</td>
<td>6888</td>
<td>6889</td>
<td>7001</td>
<td>6804</td>
<td>5822</td>
</tr>
<tr>
<td>M 10.2003</td>
<td>6888</td>
<td>6889</td>
<td>7001</td>
<td>6804</td>
<td>5822</td>
</tr>
<tr>
<td>M 11.2003</td>
<td>6888</td>
<td>6889</td>
<td>7001</td>
<td>6804</td>
<td>5822</td>
</tr>
<tr>
<td>M 12.2003</td>
<td>6888</td>
<td>6889</td>
<td>7001</td>
<td>6804</td>
<td>5822</td>
</tr>
<tr>
<td>M 01.2004</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
</tr>
<tr>
<td>M 02.2004</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
</tr>
<tr>
<td>M 03.2004</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
</tr>
<tr>
<td>M 04.2004</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
</tr>
<tr>
<td>M 05.2004</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
</tr>
<tr>
<td>M 06.2004</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
<td>6888</td>
</tr>
</tbody>
</table>

Season: 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00

Trend: 6888.40 6888.40 6888.40 6888.40 6888.40 6888.40 6888.40 6888.40 6888.40 6888.40

Diagram showing the comparison between statistical forecast and adjusted sales history.
The system automatically adjusts the alpha factor based on the initial alpha and the smallest tracking signal.

\[ \alpha_i = \alpha_{i-1} + 0.2 \times [TS - \alpha_{i-1}] \]

- TS is the tracking signal.
- TS = 0 if MAD(i) = 0.
- TS = \text{ABS} [ET(i) / \text{MAD}(i)] if MAD(i) \neq 0.
- i = 1 \ldots n, where n is the number of periods in the ex-post forecast.
- \(\alpha_i\) is used to calculate the ex-post forecast in the period i+1.
Two models are within the Moving Average group

**Moving Average (13)** -- the forecast equals the average of the historical periods

**Weighted Moving Average (14)** – the forecast equals the weighted average of the historical periods. The weighting is defined via a weighting profile.

<table>
<thead>
<tr>
<th>Period</th>
<th>Weighting</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5</td>
<td>10%</td>
</tr>
<tr>
<td>-4</td>
<td>20%</td>
</tr>
<tr>
<td>-3</td>
<td>30%</td>
</tr>
<tr>
<td>-2</td>
<td>40%</td>
</tr>
<tr>
<td>-1</td>
<td>50%</td>
</tr>
</tbody>
</table>
Moving Average-13

\[ M = \frac{\sum_{t=1}^{n} V(t)}{n} \]

- \( M \) = Average value
- \( V \) = Actual value
- \( W \) = Weighting factor
- \( n \) = Number of periods in the weighting group

Weighted Moving Average-14

\[ M = \frac{\sum_{t=1}^{n} W_t \times V_t}{\sum_{t=1}^{n} W_t} \]

No ex-post forecast calculated
Trend Models

There are four models for data with trend:

- Forecast with Trend Model (20)
- Holt's Method (21)
- Second Order Exponential Smoothing (22)
- Trend model with Automatic Alpha Adaptation (2nd order) (23)

\[ 20 = 21 \]
Holt’s Method (20, 21)

Formulas

Forecast value for period \((t + 1)\)  
\[ P(t+i) = G(t) + i \times T(t) \]

Basic Value  
\[ G(t) = \alpha V(t) + (1 - \alpha) \left[ G(t-1) + T(t-1) \right] \]

Trend Value  
\[ T(t) = \beta \left[ (G(t) - G(t-1)) + (1 - \beta)T(t-1) \right] \]

- **\(P(t+i)\)** = The forecast calculated for the period \((t+i)\) in the current period \((t)\)
- **\(i\)** = Forecast horizon
- **\(G(t)\)** = The current basic value for the current period \((t)\)
- **\(G(t-1)\)** = The previous basic value from the previous period
- **\(V(t)\)** = Actual demand (history) for the current period \((t)\)
- **\(T(t)\)** = The current trend value calculated for the current period
- **\(T(t-1)\)** = The previous trend value from the previous period
- **\(\alpha\)** = Smoothing factor for the basic value 'G'
- **\(\beta\)** = Smoothing factor for the trend value 'T'
Second Order Exponential Smoothing (22)

Encompasses a double smoothing method where the basic value of the first calculation is used as the input for the second. The result is a basic value that is more reactive to changes in demand while minimizing the trend effect.

Formulas for Second-Order Exponential Smoothing

\[
G^{(1)}(t) = \alpha V(t) + (1-\alpha) G^{(1)}(t-1)
\]

\[
G^{(2)}(t) = \alpha G^{(1)}(t) + (1-\alpha) G^{(2)}(t-1)
\]

\[
G^{(1)} = \text{Simply smoothed basic value}
\]

\[
G^{(2)} = \text{Doubly smoothed basic value}
\]

\[
V = \text{Historical value}
\]

\[
\alpha = \text{Smoothing factor}
\]
Trend with Automatic Alpha Adaptation (2nd order) (23)

This is the same as Second Order Exponential Smoothing except the systems determines the Alpha value. The minimum Alpha is 0.05 and the maximum is 0.90. The system determines the Alpha factor through an iterative processes of comparing the MAD to the Error Total (ET). (Same Method as Constant with Automatic Alpha Adaptation).

\[ \alpha_i = \alpha_{(i-1)} + 0.2 \times [TS - \alpha_{(i-1)}] \]

- TS is the tracking signal.
- TS = 0 if MAD(i) = 0.
- TS = ABS [ET (i) / MAD (i)] if MAD (i) ≠ 0.
- \(i = 1 \ldots n\), where \(n\) is the number of periods in the ex-post forecast.
- \(\alpha_i\) is used to calculate the ex-post forecast in the period i+1.
Trend Dampening Profile

As the historical values do not show a decrease in trend as the market matures, a Trend Dampening profile can be used to smooth out the trend.
Seasonal Models are used to depict a Seasonal forecast or a recurring pattern, without any upwards or downwards slope. The pattern occurs across its season or a number of Seasonal Periods (Usually recommended to be 12 Months). The trend value and Beta in this case are zero, signifying no upward or downward slope.
Seasonal Models

There are three Models associated with the seasonal patterns.

Forecast with the Seasonal Model (30)
Seasonal Trend based on the Winter’s Method (31)
Season + Linear Regression (35)

Same Formula! 
30 = 31
This model uses first order exponential smoothing where both Alpha and Gamma are assigned.

Forecast value for the period \((t+i)\)

\[ P(t+i) = (G(t)) \times S(t-L+i) \]

where:

Basic value:

\[ G(t) = G(t-1) + \alpha \left[ \frac{V(t)}{S(t-L)} \cdot G(t-1) \right] \]

Seasonal index:

\[ S(t) = S(t-L) + \gamma \left[ \frac{V(t)}{G(t)} - S(t-L) \right] \]
Season + Linear Regression (35)

- Seasonal indices calculated
- Seasonality removed from data
- Forecast created using linear regression
- Seasonality added back to forecast
There are two Models for the Seasonal Trend method:

- Forecast with Seasonal Trend Model (40)
- First Order Exponential Smoothing (41)

Same Formula! \[ 40 = 41 \]

Also know as: Holt-Winters Method
And Triple Exponential Smoothing
First Order Exponential Smoothing (40, 41)

This Model encompasses the same Formula as 20,21,30,31 and uses assigned values for the Alpha, Beta and Gamma Coefficients.

\[
P(t+i) = (G(t) + i \cdot T(t)) \cdot S(t-L+i)
\]

where:

**Basic value:**

\[
G(t) = G(t-1) + T(t-1) + \alpha \left[ \frac{V(t)}{S(t-L)} \cdot G(t-1) - T(t-1) \right]
\]

**Trend value:**

\[
T(t) = T(t-1) + \beta \left[ G(t) - (G(t-1) + T(t-1)) \right]
\]

**Seasonal index:**

\[
S(t) = S(t-L) + \gamma \left[ \frac{V(t)}{G(t)} - S(t-L) \right]
\]
Auto Selection Models

Auto Selection 1 (50)
Test for Trend and Season (53)
Test for Trend (51)
Test for Season (52)
Seasonal model plus test for Trend (54)
Trend Model plus test for Seasonal Pattern (55)
Auto Model Selection procedure 2 (56)

\[
\text{Same Formula!} \\
50 = 53
\]
Tests for Both Seasonal and Trend Patterns.

Seasonal Test: The Auto Correlation Coefficient is Calculated, the Pattern is determined to be Seasonal if the Auto Correlation Coefficient is Greater than 0.3.

**Formula for Autocorrelation Coefficient**

\[
R(p) = \frac{1}{n-p} \sum_{i=1}^{n-p} [ (V(i) - M)^*(V(i+p) - M) ]
\]

where:
- \( V(i) \) = Historical value in period \( i \)
- \( V(i+p) \) = Historical value in period \( i+p \)
- \( M \) = Average
- \( n \) = Number of historical values
- \( p \) = Number of periods per season
A Trend Significance test is carried out

Formula for Trend Significance Test

\[
P = \frac{\sqrt{\sum (V \cdot V) - \frac{1}{n} \sum (V) \cdot \sum (V) - b \cdot b \cdot \sum (T \cdot T)}}{\sqrt{n - 2} \cdot \sum (T \cdot T)}
\]

where:
\[T(i) = \frac{2 \cdot i - n - 1}{2}\]

- \(n\) = Number of historical values
- \(b\) = Trend value
- \(V\) = Historical value

If both are determined to be significant, a Seasonal Trend Model is used.

If neither tests is determined to be Significant, then the Constant Model is chosen as a default.
Test for Trend (51)

Used to Test only for Trend.

This follows the Trend Significance test previously defined. If no Significance is found then a Constant Model is Chosen.

Formula for Trend Significance Test

\[ P = \left| b \right| \sqrt{\frac{\sum (V^2) - 1/n \sum (V) \sum (V) - b \cdot b \sum (T^2)}{(n - 2) \sum (T^2)}} \]

where:
\[ T(i) = (2 \cdot i - n - 1)/2 \]

- \( n \) = Number of historical values
- \( b \) = Trend value
- \( V \) = Historical value
Used to Test only for Seasonal Pattern.

This follows the AutoCorrelation Coefficient Test and chooses the Seasonal Model if the value is above 0.3. If not a Constant Model is chosen.

**Formula for Autocorrelation Coefficient**

\[
R(p) = \frac{1}{n - p} \sum_{1}^{n} \left[ \frac{(V(i) - M)(V(i+p) - M)}{n} \right]
\]

where:
- \( V(i) \) = Historical value in period \( i \)
- \( V(i+p) \) = Historical value in period \( i+p \)
- \( M \) = Average
- \( n \) = Number of historical values
- \( p \) = Number of periods per season
Assumes Seasonal pattern exists and tests for Trend pattern. If a trend significance is found, then a Seasonal Trend Model is used. If no significance is found than a Seasonal Model is used.

**Formula for Trend Significance Test**

\[
P = \frac{I \cdot b}{\sqrt{\sum (V \cdot V) - \frac{1}{n} \sum (V) \sum (V) - b \cdot b \sum (T \cdot T)}}
\]

where:

\[
T(i) = \frac{(2 \cdot i - n - 1)}{2}
\]

- \(n\) = Number of historical values
- \(b\) = Trend value
- \(V\) = Historical value
Trend Model plus test for Seasonal Pattern (55)

Assumes Trend exists and test for a Seasonal Pattern. If the Autocorrelation Coefficient is greater than 0.3 than a Seasonal Trend Model is used, if the Seasonal test is not found to be Significant than a Trend Model is used.

Formulas for Autocorrelation Coefficient

\[ R(p) = \frac{1}{n - p} \times \sum \left[ \frac{(V(i) - M)(V(i+p) - M)}{n} \right] \]

where:
- \( V(i) \) = Historical value in period i
- \( V(i+p) \) = Historical value in period i+p
- \( M \) = Average
- \( n \) = Number of historical values
- \( p \) = Number of periods per season
Summary of the Automodel 1 selection process

This shows the Model chosen under the following Conditions:

<table>
<thead>
<tr>
<th>Automodel</th>
<th>If:Trend</th>
<th>If: Season</th>
<th>Then:Uses Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>50 - Auto Selection 1 or 53 - Test for Trend and Season</td>
<td>No</td>
<td>No</td>
<td>10 - Constant</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>20 - Trend</td>
</tr>
<tr>
<td>51 - Test for Trend</td>
<td>Yes</td>
<td>N/A</td>
<td>30 - Trend</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>Yes</td>
<td>10 - Constant</td>
</tr>
<tr>
<td>52 - Test for Season</td>
<td>N/A</td>
<td>Yes</td>
<td>30 - Season</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>10 - Constant</td>
</tr>
<tr>
<td>54 - Seasonal Model plus test for Trend</td>
<td>No</td>
<td>Yes by Default</td>
<td>30 - Season</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td></td>
<td>40 - Seasonal Trend</td>
</tr>
<tr>
<td>55 - Trend Model plus test for Season</td>
<td>Yes by Default</td>
<td>Yes</td>
<td>40 - Seasonal Trend</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>20 - Trend</td>
</tr>
</tbody>
</table>
Tests for Constant, Seasonal and/or Trend models while attempting to minimize Error by adjusting Alpha, Beta and Gamma.

This model adjusts Alpha, Beta and Gamma between the values of 0.1 to 0.5 in 0.1 increments while calculating the Mean Absolute Deviation (MAD) for each Iteration. The iteration with the Lowest MAD is the Model chosen with the appropriate smoothing factors.
# Auto Selection Model 1 & Auto Selection Model 2

<table>
<thead>
<tr>
<th>Determines Seasonal and Trend Significance through Formulas for Auto Correlation (Seasonal Significance) and Trend Significance Tests</th>
<th>Determines Best Fit through through Iterative approach of adjusting smoothing factors (Alpha, Beta, Gamma) and determining Smallest Mean Absolute Deviation (MAD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not as precise as Auto Model 2</td>
<td>Resource Intensive (Not recommended for Production use)</td>
</tr>
<tr>
<td>If no Pattern Detected defaults Constant Model</td>
<td>Chooses Best Fit of Constant, Trend, Seasonal, Seasonal Trend.</td>
</tr>
</tbody>
</table>
The Croston Model (80) is used when demand is sporadic or intermittent. The return is a Constant model to meet the possible sporadic demand.
The Historical Data Model (60) allows you to use your Historical values as your forecast.
The Manual Forecast (70) allows the planner to set their own values to generate a forecast. The values chosen are all the values that make up the forecast; these are the smoothing coefficients Alpha, Beta, Gamma (from the Profile) and the Basic, Trend value and Seasonal Index. This model should not be used for Background Processing.
No forecast is conducted
It is also possible to define your own Forecasting model if the model you commonly use is not provided. The external Forecasting feature allows you to use ABAP to code your own forecasting model.
**Explanation of the Variables**

\[
P(t+i) = \text{The forecast calculated for the period } (t+i) \text{ in the current period } (t)
\]

\[
i = \text{Forecast horizon}
\]

\[
G(t) = \text{The current basic value for the current period } (t)
\]

\[
G(t-1) = \text{The previous basic value from the previous period}
\]

\[
L = \text{Period length (often 12)}
\]

\[
\alpha = \text{Smoothing factor for the basic value } 'G', 0 < \alpha < 1
\]

\[
\beta = \text{Smoothing factor for the trend value } 'T', 0 < \beta < 1
\]

\[
\gamma = \text{Smoothing factor for the seasonal indices } 'S', 0 < \gamma < 1
\]

\[
V(t) = \text{Actual demand (history) for the current period } (t)
\]

\[
T(t) = \text{The current trend value calculated for the current period}
\]

\[
T(t-1) = \text{The previous trend value from the previous period}
\]

\[
S(t) = \text{The seasonal index for the period } (t)
\]

\[
S(t-L) = \text{The previous seasonal index for the period } (t)
\]
Univariate Forecast Basics

Univariate Models in APO

Forecast Error Analysis
Forecast Accuracy Measurements

Mean Absolute Deviation (MAD)

Error Total (ET)

Mean Absolute Percentage Error (MAPE)

Mean Square Error (MSE)

Square Root of the Mean Squared Error (RMSE)

Mean Percentage Error (MPE)
Mean Absolute Deviation (MAD)

The Mean Absolute Deviation is calculated by the absolute difference between the ex-post forecast and the actual value.

$$\text{MAD}(t) = (1 - \delta) \times \text{MAD}(t-1) + \delta \times |V(t) - P(t)|$$

Key to MAD Formula

- $V(t) = \text{Actual value}$
- $P(t) = \text{Forecast value}$
- $\delta = 0.3$

The Mean Absolute Deviation is the error calculation used to determine the best fit in the Auto Model 2 Forecasting Model.
The Error Total is the sum of the difference between the Actual and the Ex-post forecast.

\[ ET = \sum_{t=1}^{n} [V(t) - P(t)] \]

Key to Error Total Formula

- \( V(t) \) = Actual value
- \( P(t) \) = Forecast value
- \( n \) = Number of ex-post periods
The Mean Square Error is the Average of the sum of the square of each difference between the ex-post forecast and the Actual value.

\[
\text{MSE} = \frac{1}{n} \sum_{t=1}^{n} e(t)^2
\]

**Key to MSE Formula**

\[ e(t) = V(t) - P(t) \]
\[ V(t) = \text{Actual value} \]
\[ P(t) = \text{Forecast value} \]
\[ n = \text{Number of ex-post periods} \]
The Mean Absolute Percentage Error is the Average Absolute Percent Error between the Actual Values and their corresponding Ex-post Forecast Values.

\[
\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} |P(t) - V(t)|
\]

Key to MAPE Formula

\[
\begin{align*}
\text{PE}(t) &= \frac{e(t)}{V(t)} \times 100 \\
e(t) &= V(t) - P(t) \\
V(t) &= \text{Actual value} \\
P(t) &= \text{Forecast value} \\
n &= \text{Number of ex-post periods}
\end{align*}
\]
Root mean Square Error (RMSE)

The Root Mean Square Error is the Square root of the average of the sum of the squared difference between the Actual and Ex-post Forecast value.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} e(t)^2}
\]

Key to RMSE Formula

- \( e(t) = V(t) - P(t) \)
- \( V(t) = \text{Actual value} \)
- \( P(t) = \text{Forecast value} \)
- \( n = \text{Number of ex-post periods} \)
Mean Percentage Error (MPE)

The Mean Percentage Error is the average percentage error of the difference between the Ex-post Forecast and the Actual values.

\[
MPE = \frac{1}{n} \sum_{t=1}^{n} PE(t)
\]

Key to MPE Formula

\[
PE(t) = \frac{e(t)}{V(t)} \times 100
\]

\[
e(t) = V(t) - P(t)
\]

\[
V(t) = \text{Actual value}
\]

\[
P(t) = \text{Forecast value}
\]

\[
n = \text{Number of ex-post periods}
\]
Thank You