Improving Supply Chain Planning with Advanced Analytics

Analyzing Lead Time as a Case Study

Presented By: Darryl Yau
Advised By: Dr. Christopher Caplice

Research Fest 2018
# My Typical Schedule

- **Always at my meetings**
- **100% adherence to schedule**
- **100% On Time Delivery (OTD)**

### May 2018

<table>
<thead>
<tr>
<th>Date</th>
<th>Monday (5:00pm)</th>
<th>Tuesday (5:00pm)</th>
<th>Wednesday (5:00pm)</th>
<th>Thursday (5:00pm)</th>
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<td>Event L</td>
<td>Event M</td>
<td>Event N</td>
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<td>Event Q</td>
<td>Event R</td>
<td>Event S</td>
<td>Event T</td>
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<td>5:00pm</td>
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<td>Event U</td>
<td>Event V</td>
<td>Event W</td>
<td>Event X</td>
<td>Event Y</td>
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Supply Chain Example

*BUT*...100% adherence to schedule within the supply chain context is almost unheard of

<table>
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<tr>
<th>Period</th>
<th>0</th>
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<th>2</th>
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<td>50</td>
<td>100</td>
<td>50</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Production Plan</td>
<td>50</td>
<td>100</td>
<td>50</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Actual Production</td>
<td>40</td>
<td>90</td>
<td>80</td>
<td>20</td>
<td>120</td>
</tr>
<tr>
<td></td>
<td>-10</td>
<td>-20</td>
<td>+10</td>
<td>-20</td>
<td>0</td>
</tr>
</tbody>
</table>

Supply Chain is very *complex*!
What can we do?

- Force operations to conform to the schedule
- Create a schedule that is more accurate
Many parameters used during planning process are not given the proper attention it deserves

Consider:

- Values that were not scientifically or accurately set in the first place
- Values that have changed or are changing over time

How do we create a ‘self-healing’ supply chain?
To what extent are the lead time variables found in the Enterprise Resource Planning (ERP) system are used in predicting lead time and how accurate is the prediction?

Can predictive analytics on historical lead time data be used to improve the forecast accuracy and what are the benefits in doing so?
Number of Entries over Time

- Over 4M Line Items (500,000+ Purchase Orders)
- Over 80,000 SKUs
Understanding Different Lead Time Variables Along the Planning Process

Planning Process

- Standard Lead-Time Variables
  - Lead Time by SKU and Vendor (LT_v)
  - Lead Time by SKU and Plant (LT_p)

- When Order is Placed
- When Order is Received

- Other Business Constraints/Decisions

Planned Lead Time vs. Actual Lead Time

How can the accuracy be improved?
Conceptualizing How Planned Lead Time is Formulated

\[ \text{Planned Lead Time}_{\text{SKU} - \text{Lane}=V1P1} = \beta_0 + \beta_1LT_{P1} + \beta_2LT_{V1} + \epsilon \]

Where: 
- \( \beta_i = \) coefficients
- \( \epsilon = \) error or unexplained term

**Lead Time based on SKU and Vendor**

- Lead Time by SKU and Vendor (LT

**Lead Time based on SKU and Plant**

- Lead Time by SKU and Plant (LT

**How can the accuracy be improved?**

**Vendors**

- V1

**Plant**

- P1
- P2
- P3
Today’s Agenda

1. Background

2. Data

3. Analysis and Results

4. Conclusion
Improving Supply Chain Planning with Advanced Analytics
Analyzing Lead Time as a Case Study

1. Baseline Current State
   To what extent are the lead time variables found in the Enterprise Resource Planning (ERP) system used in predicting lead time and how accurate is the prediction?

2. Propose Improved Future State
   Can predictive analytics on historical lead time data be used to improve the forecast accuracy and what are the benefits in doing so?
**Regression Performed Across the Entire Dataset**

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable</th>
<th>Intercept ($\beta_0$)</th>
<th>SKU and Vendor ($LT_v$) ($\beta_1$)</th>
<th>SKU and Plant ($LT_p$) ($\beta_2$)</th>
<th>Adjusted $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All</strong></td>
<td>Planned Lead Time</td>
<td>7.086</td>
<td>0.064</td>
<td>0.853</td>
<td>0.253</td>
</tr>
<tr>
<td></td>
<td>Actual Lead Time</td>
<td>7.953</td>
<td>0.224</td>
<td>0.718</td>
<td>0.155</td>
</tr>
<tr>
<td><strong>2004-2007</strong></td>
<td>Planned Lead Time</td>
<td>15.827</td>
<td>-0.340</td>
<td>0.051</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>Actual Lead Time</td>
<td>86.269</td>
<td>-2.666</td>
<td>0.049</td>
<td>0.005</td>
</tr>
<tr>
<td><strong>2008-2011</strong></td>
<td>Planned Lead Time</td>
<td>20.798</td>
<td>-0.236</td>
<td>0.328</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>Actual Lead Time</td>
<td>73.426</td>
<td>-1.445</td>
<td>0.376</td>
<td>0.014</td>
</tr>
<tr>
<td><strong>2012-2015</strong></td>
<td>Planned Lead Time</td>
<td>7.314</td>
<td>0.089</td>
<td>0.909</td>
<td>0.266</td>
</tr>
<tr>
<td></td>
<td>Actual Lead Time</td>
<td>7.042</td>
<td>0.221</td>
<td>0.811</td>
<td>0.204</td>
</tr>
<tr>
<td><strong>2016-2017</strong></td>
<td>Planned Lead Time</td>
<td>5.661</td>
<td>0.073</td>
<td>1.122</td>
<td>0.406</td>
</tr>
<tr>
<td></td>
<td>Actual Lead Time</td>
<td>7.537</td>
<td>0.191</td>
<td>0.879</td>
<td>0.249</td>
</tr>
</tbody>
</table>

- Poor $R^2$ values
- Seems to improve over time
- $R^2$ values for Actual Lead Time consistently worse than $R^2$ for Planned Lead Time
Vendor and Plant appears to be factors contributing to the variability of actual lead time.

Note: Using one SKU as an example.
Analyses performed at the SKU–Lane level

Lane = Unique Vendor and Plant Combination

Vendors (200+)

Lanes (500+)

Plants (20+)

V1

V2

V3

... 

Vn

L1

L2

L3

L4

L5

L6

L7

L8

Ln

P1

P2

P3

... 

Pn
**t Test — Null Hypothesis: Are these datasets statistically the same?**

- Ran t test on over 25,000 SKU-Lanes
  - For LTv and Planned Lead Time
  - For LTp and Planned Lead Time
  - Planned Lead Time and Actual Lead Time

- NOT the same for all tests
Improving Supply Chain Planning with Advanced Analytics
Analyzing Lead Time as a Case Study

1. Baseline Current State

To what extent are the lead time variables found in the Enterprise Resource Planning (ERP) system used in predicting lead time and how accurate is the prediction?

2. Propose Improved Future State

The standard lead time variables (LTv and LTp) are not good predictors for what is planned.

The planned lead times are not good predictors for what actually happens.

Can predictive analytics on historical lead time data be used to improve the forecast accuracy and what are the benefits in doing so?
Improving Supply Chain Planning with Advanced Analytics
Analyzing Lead Time as a Case Study

1. Baseline Current State

To what extent are the lead time variables found in the Enterprise Resource Planning (ERP) system are used in predicting lead time and how accurate is the prediction?

2. Propose Improved Future State

Can predictive analytics on historical lead time data be used to improve the forecast accuracy and what are the benefits in doing so?
# Time Series Analysis — Forecasting Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method 1 – Naïve</td>
<td>Only the last data point is considered.</td>
<td>$\hat{x}_{t,t+1} = x_t$</td>
</tr>
<tr>
<td>Method 2 – Simple Mean</td>
<td>All the data points are considered. Any trend in the underlying data will lead to severe lagging.</td>
<td>$\hat{x}<em>{t,t+1} = \frac{\sum</em>{i=1}^{t} x_i}{t}$</td>
</tr>
<tr>
<td>Method 3 – Moving Average</td>
<td>Only the last n data points are considered.</td>
<td>$\hat{x}<em>{t,t+1} = \frac{\sum</em>{i=t+1-n}^{t} x_i}{n}$</td>
</tr>
<tr>
<td>Method 4 – Single Exponential Smoothing</td>
<td>This model is used to capture level of the time series. However, data is treated differently depending on its age.</td>
<td>$\hat{x}<em>{t,t+1} = ax_t + (1-a)\hat{x}</em>{t-1,t}$</td>
</tr>
</tbody>
</table>
| Method 5 – Holt’s Method (level and trend) | This model is used to forecast time series with a linear trend. A form of exponential smoothing, a higher weight is given to data that is more recent. | $\hat{x}_{t,t+T} = \hat{a}_t + \tau \hat{b}_t$
$\hat{a}_t = ax_t + (1-a)(\hat{a}_{t-1} + \hat{b}_{t-1})$
$\hat{b}_t = \beta(\hat{a}_t-\hat{a}_{t-1}) + (1-\beta)\hat{b}_{t-1}$ |
| Method 6 – Holt-Winter’s Method (level, trend, and seasonality) | Model is used to forecast time series with both a linear trend and seasonality. A form of exponential smoothing, a higher weight is given to data that is more recent. | $\hat{x}_{t,t+T} = \hat{a}_t + \tau \hat{b}_t + \hat{F}_{t,T+\tau}$
$\hat{a}_t = a(\frac{x_t}{F_{t-\tau}^{\hat{F}}}) + (1-a)(\hat{a}_{t-1} + \hat{b}_{t-1})$
$\hat{b}_t = \beta(\hat{a}_t-\hat{a}_{t-1}) + (1-\beta)\hat{b}_{t-1}$
$\hat{F}_t = \gamma(\frac{x_t}{\hat{a}_t}) + (1-\gamma)\hat{F}_{t-\tau}$ |
Bottom–up and Top–down Analyses

Analyses on Entire Dataset

Individual SKU–Lane Analyses
Analyzing one SKU—Lane

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Measure Names</th>
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<tr>
<td>1.0000</td>
<td>Actual Lead Time</td>
</tr>
<tr>
<td>5.0000</td>
<td>Planned Lead Time</td>
</tr>
<tr>
<td>10.0000</td>
<td></td>
</tr>
<tr>
<td>15.0000</td>
<td></td>
</tr>
<tr>
<td>20.0000</td>
<td></td>
</tr>
<tr>
<td>25.0000</td>
<td></td>
</tr>
</tbody>
</table>

Actual Received Date

Autocorrelation

Lag

Actual Delivery Date

Measure Names
- Rolling Mean (22 Weeks)
- Rolling STD (22 Weeks)
- Actual Lead Time
Forecasting on One SKU—Lane

Legend
- Planned LT
- Regression
- Naive
- Simple Mean
- MA (n=5)
- MA (n=10)
- SES
- Holts
- Holt-Winter's

Set Type
- Testing Set
- Training Set

Analysis and Results

Data

Conclusion
### Forecasting on One SKU—Lane

<table>
<thead>
<tr>
<th></th>
<th>Mean (Days)</th>
<th>Coefficient of Variation</th>
<th>Standard Deviation (Days)</th>
<th>Mean Deviation (MD) (Days)</th>
<th>Mean Average Deviation (MAD) (Days)</th>
<th>Mean Absolute Percent Error (MAPE)</th>
<th>Root Mean Squared Error (RMSE) (Days)</th>
<th>Mean Percent Error (MPE)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline 1: Planned Lead Time</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>9.23</td>
<td>0.49</td>
<td>4.56</td>
<td>-1.34</td>
<td>1.40</td>
<td>18.45%</td>
<td>1.85</td>
<td>-17.71%</td>
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<td><strong>Baseline 2: Regression Analysis</strong></td>
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<tr>
<td></td>
<td>8.98</td>
<td>0.00</td>
<td>0.00</td>
<td>-1.09</td>
<td>3.21</td>
<td>46.42%</td>
<td>3.84</td>
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<td><strong>Naive Approach</strong></td>
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<td></td>
<td>8.13</td>
<td>0.50</td>
<td>4.05</td>
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<td>1.29</td>
<td>24.12%</td>
<td><strong>2.81</strong></td>
<td>-10.29%</td>
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<td><strong>Simple Mean Approach</strong></td>
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<td></td>
<td>8.00</td>
<td>0.01</td>
<td>0.04</td>
<td>-0.11</td>
<td>2.63</td>
<td>34.88%</td>
<td>3.70</td>
<td>-18.58%</td>
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<td><strong>Moving Average (n=5)</strong></td>
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<tr>
<td></td>
<td>8.81</td>
<td>0.45</td>
<td>4.00</td>
<td>-0.93</td>
<td>2.45</td>
<td>44.73%</td>
<td>3.96</td>
<td>-27.59%</td>
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<tr>
<td><strong>Moving Average (n=10)</strong></td>
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<td>9.34</td>
<td>0.34</td>
<td>3.16</td>
<td>-1.45</td>
<td>3.40</td>
<td>56.61%</td>
<td>4.62</td>
<td>-40.09%</td>
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<td><strong>Simple Exponential Smoothing (α = 0.1)</strong></td>
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<tr>
<td></td>
<td>9.53</td>
<td>0.20</td>
<td>1.93</td>
<td>-1.64</td>
<td>3.28</td>
<td>52.86%</td>
<td>3.93</td>
<td>-40.89%</td>
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<tr>
<td><strong>Holt’s Method (α = 0.2 β=0.05)</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>9.13</td>
<td>0.39</td>
<td>3.55</td>
<td>-1.24</td>
<td>2.59</td>
<td>45.94%</td>
<td>4.08</td>
<td>-33.51%</td>
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<tr>
<td><strong>Holt-Winter’s Method (α = 0.2 β=0.05 γ=0.1)</strong></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>8.66</td>
<td>0.36</td>
<td>3.12</td>
<td>-0.77</td>
<td>2.21</td>
<td>37.33%</td>
<td>3.00</td>
<td>-22.62%</td>
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</tbody>
</table>
Bottom–up and Top–down Analyses

- Analyses on Entire Dataset
- Individual SKU–Lane Analyses
### Analysis of Entire Dataset

#### Background

- Ran for over 2,500 SKU-Lane Combinations
- Best Forecast Method had a lower average MAPE than both baselines
- Using a single method had a lower average MAPE than both baselines

#### Data

- Best Forecast Method, on average, performed better than both baselines

#### Analysis and Results

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean MAPE</th>
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<tbody>
<tr>
<td>Baseline 1: Planned Lead Time</td>
<td>24.9%</td>
</tr>
<tr>
<td>Baseline 2: Regression Analysis</td>
<td>12.4%</td>
</tr>
<tr>
<td>Best Forecast Method</td>
<td>14.5%</td>
</tr>
<tr>
<td>Naive</td>
<td>18.6%</td>
</tr>
<tr>
<td>Simple Mean</td>
<td>15.3%</td>
</tr>
<tr>
<td>MA (3)</td>
<td>15.4%</td>
</tr>
<tr>
<td>MA (10)</td>
<td>15.2%</td>
</tr>
<tr>
<td>SES</td>
<td>15.2%</td>
</tr>
<tr>
<td>Holt’s</td>
<td>15.0%</td>
</tr>
<tr>
<td>Holt–Winter’s</td>
<td></td>
</tr>
</tbody>
</table>

#### Conclusion

- Which had the Lower RMSE Result? (Forecast Method vs Baselines)

- Best Forecast Method, on average, performed better than both baselines
Which Forecast Method?

Forecast Method with the Lowest RMSE Value (gaps not filled)

- Holt-Winter’s Method regularly performed better than other methods
- Holt’s Method regularly performed worse than other methods
Trend did not appear to be a big factor in this dataset

Of the five SKU-Lanes that may have a trend in the data, only 1 appeared to have a significant trend.

10% Probability Series is Not Non-Stationary*

<table>
<thead>
<tr>
<th>Method</th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive</td>
<td>85.0%</td>
<td>15.0%</td>
</tr>
<tr>
<td>Simple Mean</td>
<td>96.5%</td>
<td>3.5%</td>
</tr>
<tr>
<td>MA (n=5)</td>
<td>85.4%</td>
<td>14.6%</td>
</tr>
<tr>
<td>MA (n=10)</td>
<td>87.0%</td>
<td>13.0%</td>
</tr>
<tr>
<td>SES</td>
<td>84.5%</td>
<td>15.5%</td>
</tr>
<tr>
<td>Holt’s</td>
<td>93.8%</td>
<td>6.3%</td>
</tr>
<tr>
<td>Holt–Winter’s</td>
<td>94.3%</td>
<td>5.7%</td>
</tr>
</tbody>
</table>

*Based on Dickey–Fuller Test for Stationarity
Holt–Winter’s Method appears to perform well regardless of the level of seasonality in the data.

<table>
<thead>
<tr>
<th>Seasonality Percentages* (%)</th>
<th>60</th>
<th>50</th>
<th>40</th>
<th>30</th>
<th>20</th>
<th>10</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Mean</td>
<td>33.3%</td>
<td>36.4%</td>
<td>26.5%</td>
<td>41.0%</td>
<td>44.7%</td>
<td>31.8%</td>
<td>100%</td>
</tr>
<tr>
<td>Simple Exponential Smoothing</td>
<td>66.7%</td>
<td>18.2%</td>
<td>12.2%</td>
<td>12.4%</td>
<td>4.8%</td>
<td>3.2%</td>
<td>3.9%</td>
</tr>
<tr>
<td>Naive</td>
<td>11.4%</td>
<td>18.2%</td>
<td>36.7%</td>
<td>7.9%</td>
<td>7.7%</td>
<td>8.8%</td>
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<tr>
<td>Moving Average (5)</td>
<td>9.7%</td>
<td>18.2%</td>
<td>36.7%</td>
<td>12.4%</td>
<td>7.1%</td>
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<tr>
<td>Moving Average (10)</td>
<td>8.8%</td>
<td>18.2%</td>
<td>36.7%</td>
<td>12.4%</td>
<td>7.1%</td>
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<td>11.4%</td>
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<tr>
<td>Holt’s</td>
<td>11.4%</td>
<td>18.2%</td>
<td>36.7%</td>
<td>12.4%</td>
<td>7.1%</td>
<td>11.4%</td>
<td>11.4%</td>
</tr>
<tr>
<td>Holt–Winter’s</td>
<td>8.8%</td>
<td>18.2%</td>
<td>36.7%</td>
<td>12.4%</td>
<td>7.1%</td>
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<td>11.4%</td>
</tr>
</tbody>
</table>

Holt–Winter’s Method appears to be a safe choice regardless of seasonality profile.

*Based on Time Series Decomposition
Signs of ‘Lane Profile’

<table>
<thead>
<tr>
<th>Test Type</th>
<th>Lane ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holt–Winter’s</td>
<td><img src="Image" alt="Graph" /></td>
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<tr>
<td>Simple Mean</td>
<td><img src="Image" alt="Graph" /></td>
</tr>
<tr>
<td>SES</td>
<td><img src="Image" alt="Graph" /></td>
</tr>
<tr>
<td>Holt's</td>
<td><img src="Image" alt="Graph" /></td>
</tr>
<tr>
<td>MA (5)</td>
<td><img src="Image" alt="Graph" /></td>
</tr>
<tr>
<td>MA (10)</td>
<td><img src="Image" alt="Graph" /></td>
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<tr>
<td>Naive</td>
<td><img src="Image" alt="Graph" /></td>
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</tbody>
</table>

Certain Lanes appear to favor certain forecasting methods.
Cost of item appears to be a factor in how well they currently plan

- Higher cost items have lower RMSE.
- Lower cost items have higher RMSE.
Financial Implications

\[ E[\text{safety stock cost}] = ck\sigma_{DL} \]

\[ \sigma_{DL} = \sqrt{\mu_L\sigma_D^2 + \mu_D^2\sigma_L^2} \]

Notations:
- \( c \) : unit cost ($/unit)
- \( h \) : holding rate ($/$ value/time). For this analysis, \( h \) is assumed to be 20%
- \( k \) : safety factor. For this analysis, service level is assumed to be 95%, thus \( k = 1.645 \)
- \( \sigma_{DL} \) : standard deviation of demand over lead time
- \( \sigma_D \) : standard deviation of demand \( (D) \) or lead time \( (L) \)
- \( \mu_D \) : mean of demand \( (D) \) or lead time \( (L) \)

Estimated Safety Stock Costs

Potential cost savings by reduction in their safety stock.
Bringing it together....

Planning Process

Standard Lead–Time Variables

When Order is Placed

When Order is Received

Predictive Lead Time Variable

Planned Lead Time (based on Predictive LT)

Vs.

Actual Lead Time

Accuracy Improved

Other Business Constraints/Decisions

Does not change over time

How can the accuracy be improved?
Improving Supply Chain Planning with Advanced Analytics
Analyze Lead Time as a Case Study

1. Baseline Current State

Using historical data to predict lead times can reduce the error between plan and actual

Reduces Safety Stock costs and manual labor costs

To what extent are the lead time variables found in the Enterprise Resource Planning (ERP) system are used in predicting lead time and how accurate is the prediction?

2. Propose Improved Future State

Can predictive analytics on historical lead time data be used to improve the forecast accuracy and what are the benefits in doing so?
Today’s Agenda

1. Background
2. Data
3. Analysis and Results
4. Conclusion
Conclusions and Considerations

Using Predictive Lead Time can reduce the error between plan and actual

- Safety Stock Cost
- Manual Labor in Planning and Re-Planning
- Manual Labor in PO Management

Consider:

- Assigning Forecast Method by Lane
- Implementing on High Volume, Low Cost Items
- Categorizing SKU–Lanes by Trend, Seasonality
Questions?
Backup Slides
Today’s Agenda

1. Background
2. Data
3. Analysis and Results
4. Conclusion
Industry 4.0

1.0
1784 – Mechanization, water power, steam power

2.0
1870 – Mass production, assembly line, electricity

3.0
1969 – Computer and automation

4.0
Present – Cyber physical systems / digital transformation

Important for 2 reasons:
1. Access to more data for analyses
2. Evolution of a “digital supply chain’s” role in planning
Supply Chain Planning Systems (e.g., ERP, APS) are becoming increasingly more complex in order to more accurately model the complexities of the physical supply chain.
... because a plan that does not reflect reality will much manual intervention during execution
How abstract should we conceptualize the problem?

More abstract?
- Might solve the wrong problem
- Require more manual labor to supplement the decision making process
Errors of the Third Kind

• First and Second Kind were about Accuracy – False Positive and False Negatives

• Third Kind (Mitroff, 1974) – Solving the wrong problem by choosing the wrong problem representation
  • Could be more problematic than first and second kind errors
Humans Making Decisions?

- Kahneman & Tversky, 1979
  - Prospect Theory – People make decisions based on potential value rather than the outcome

- Wu and Gonzalez, 1999
  - Further studies on Prospect Theory. Analyzed different probability weighting functions

- Schweitzer & Cachon, 2000
  - Managers consistently deviated from the optimal order point for newsvendor problem, even with feedback and additional training
To Summarize...

We need a planning process that is:

- Data Driven
- More Complex, More Like the Physical
- Less Human Intervention