Roadmap

1. Introduction to Service Supply Chains & Thesis Focus
2. Data Set Generation
3. Methodology – Time-Series Forecasting
4. Methodology – Predictive Forecasting
5. Results and Data Analysis
6. Conclusions and Implications

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- **Introduction to Service Supply Chains & IoT**
- Data Set Generation
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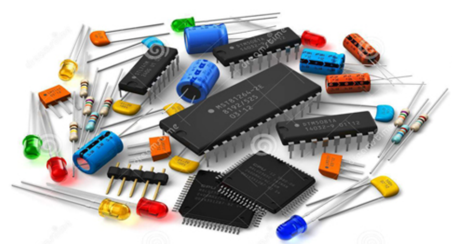
1. Service Supply Chain Introduction

- Traditional supply chains deal with flows driven by customer demand

Raw Materials Sourcing → Manufacture → Distribution → Retail → Customer

- Service supply chains deal with flows driven by product failure/customer dissatisfaction, and occur after the sale

Customer Returns / Reverse Logistics



Spare Parts Planning

Warranty management

1. http://www.fulltimefba.com/wp-content/uploads/2014/01/return-refund-image.jpg
2. http://primepower-bd.com/wp-content/uploads/2015/03/parts.jpg
3. http://autocreditcenterga.com/wp-content/uploads/2015/05/warranty.jpg

1. Service Supply Chain Financial Impact

Consumer electronics industry

On average, warranty service costs represent **6%** of total revenue

Apple

2.7% of Apple's revenue

$4.6b (2013)
$4.9b (2014)

1. Machine Data & Predictive Analytics

- Within the last 5-10 years, the number of internet connected devices (commonly known as the "Internet of Things") has exploded
- **How can companies incorporate this information into their spare parts planning process?**


Introduction to Service Supply Chains & IoT
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1. Data Set Generation

- Before comparing forecasting methods, needed to generate a demand data set to use in each of the two different methods
    - Accomplished by incorporating three different pieces of information:

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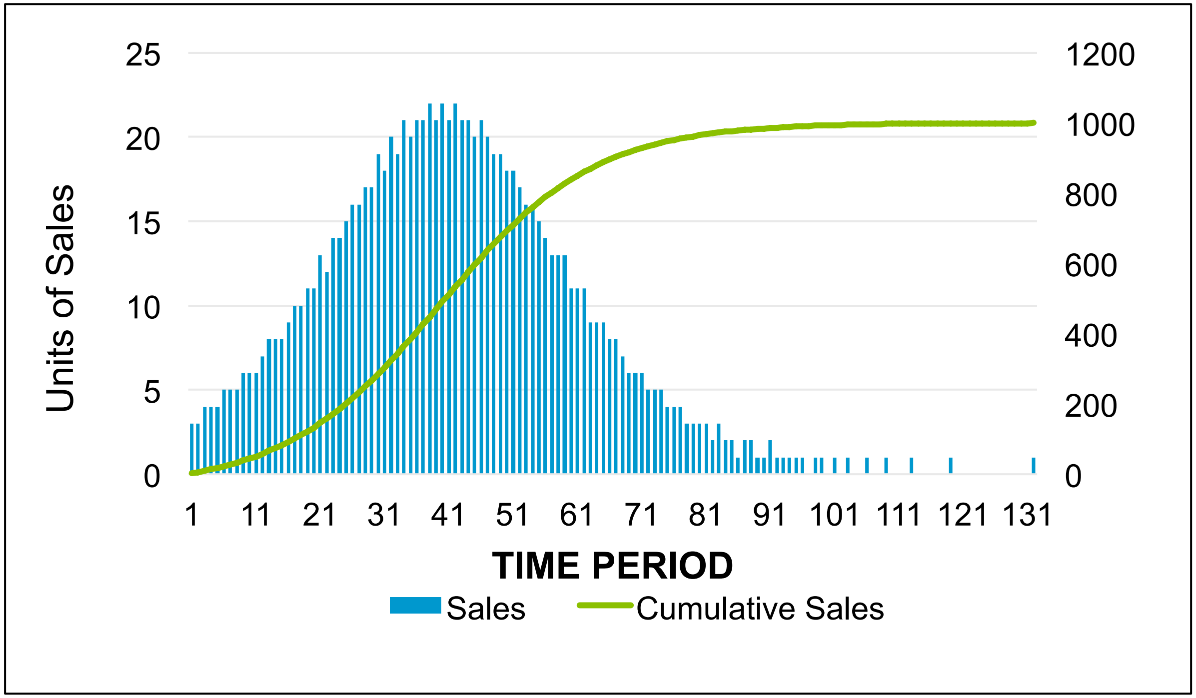
2. Data Set Generation

Sales → Warranties → Failures

- Sales are generated using the Bass Diffusion Model



$$A_t = m \times \frac{1 - e^{-((p+q)\times t)}}{1 + (\frac{q}{p} \times e^{-((p+q)\times t)})} \qquad t = 1, \ldots, n$$

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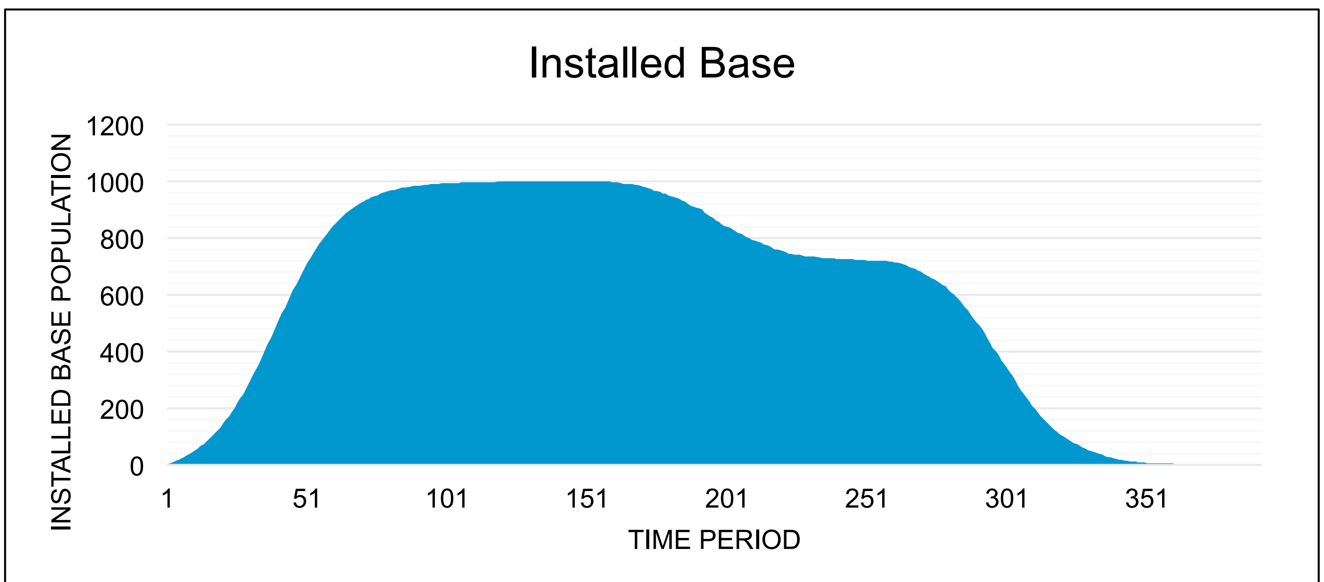
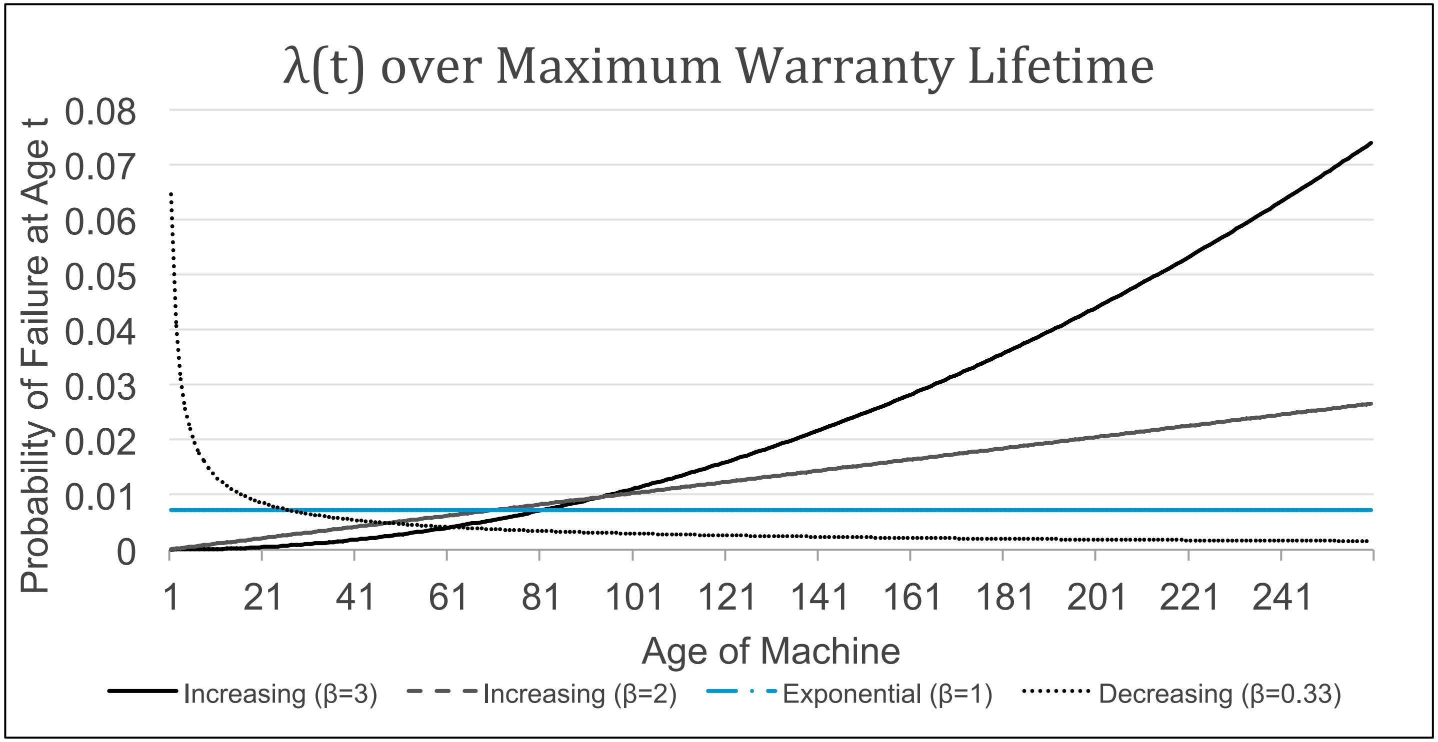
2. Data Set Generation

- Warranty periods are assigned randomly to each machine sold
- Sales and warranty information create an installed base

Warranty ID	Warranty Length (days)	Warranty Proportion of Population	Warranty Cumulative Proportion
A	156	0.3	0.3
B	260	0.7	1.0



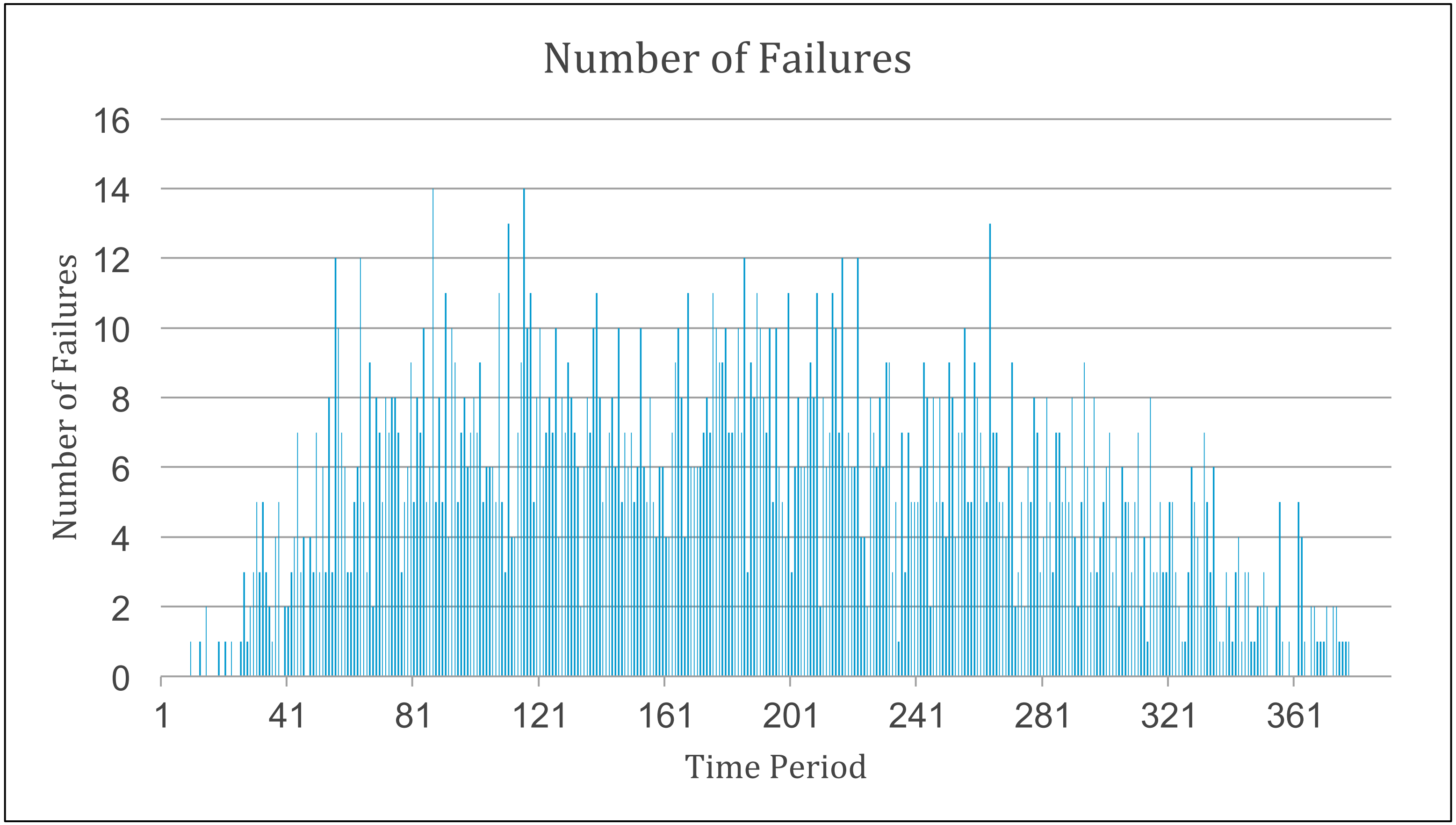
2. Data Set Generation



$$\lambda_t = \frac{\beta}{\eta} \times \left(\frac{a_{j_t} - \gamma}{\eta}\right)^{\beta - 1}$$

2. Demand Set Generation

- Installed base and failure rate function create a simulated demand statement that we can use to test the two different forecasting models



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Introduction to Service Supply Chains & IoT

Data Set Generation

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Methodology – Predictive Analytics Forecasting

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3. Time-Series Forecasting Methodology

- A time-series forecasting method forecasts future spare part demand based on the historical demand statement to date
- We evaluate two different methods of time-series forecasting:

Simple exponential smoothing

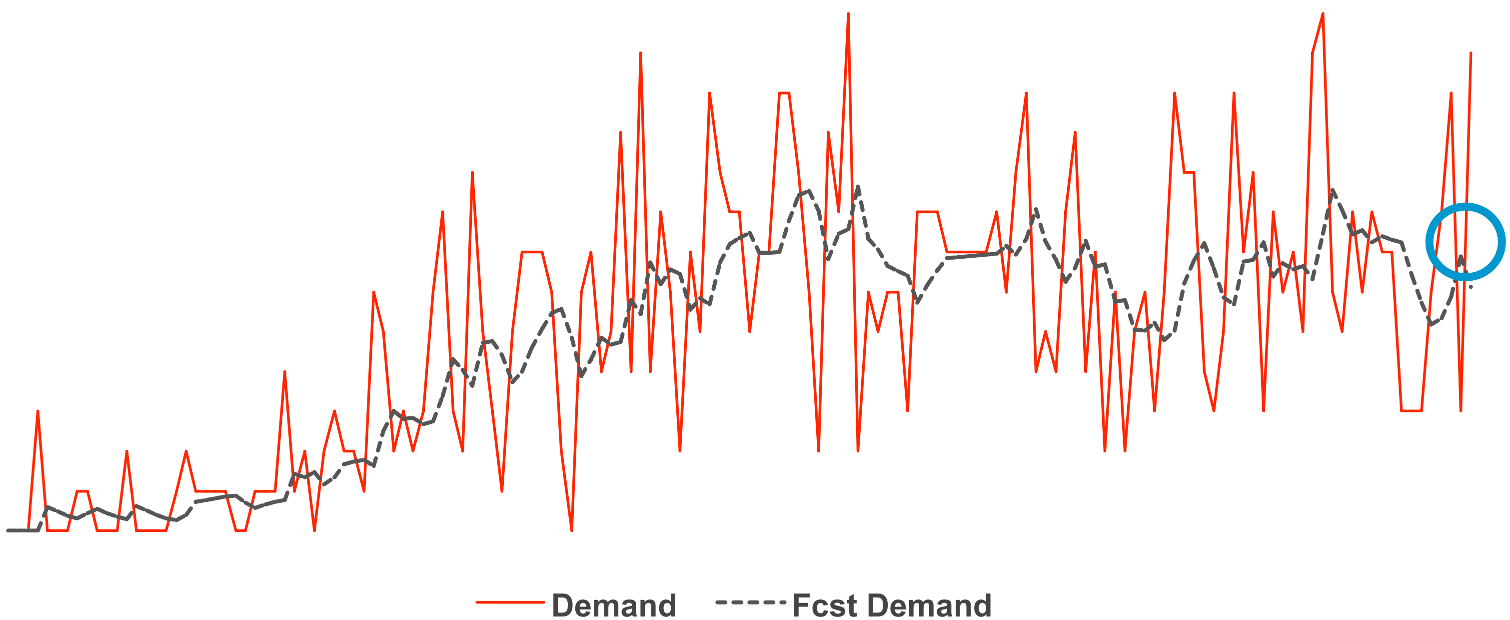
$$F_{t,t+1} = \alpha * d_t + (1-\alpha) * F_{t-1,t}$$

Simple exponential smoothing with trend

$$Ft_{t,t+1} = S_{t,t+1} + T_{t,t+1}$$

$$S_{t,t+1} = \alpha * d_t + (1-\alpha) * \left(S_{t-1,t} + T_{t-1,t}\right)$$

$$T_{t,t+1} = \beta * \left(F_{t,t+1} - F_{t-1,t}\right) + (1-\beta) * \left(T_{t-1,t}\right)$$

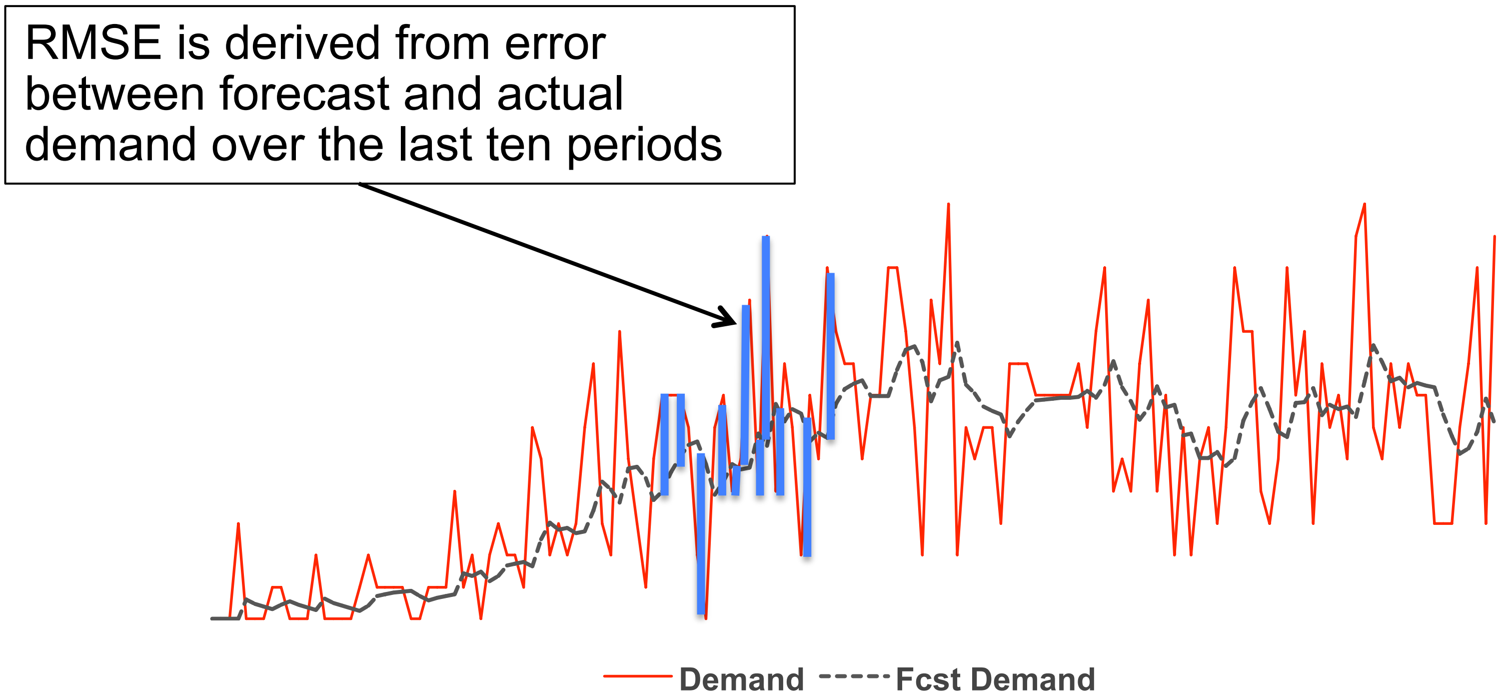


3. Time-Series Forecasting Methodology

- Forecast from time-series is plugged into R, S system
- To maintain certain level of service, we define a reorder point S. If the inventory level is under some level S, place an order of size S less the current inventory position

$$S_t = \mu_{L+R_t} + z * RMSE_{L+R_t}$$

$$Qp_t = max\,(S_t - IP_t, 0)$$

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4. Predictive Analytics Methodology

- Predictive forecasting approach runs on a binary classification matrix
  - Assumes some analysis of a set of machine data has taken place and been compared to a related set of spare parts dispatches

		predicted value: *true*	predicted value: *false*
actual value	*true*	True Positive	False Negative
	false	False Positive	True Negative

TPR *= tp / (tp+fn)*

FPR *= fp/(fp+tn)*

PPV *= tp/(tp+fp)* ***NPV*** *= tn/(fn+tn)*

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4. Predictive Analytics Methodology

		predicted value: *true*	predicted value: *false*
actual value	*true*	True Positive	False Negative
	false	False Positive	True Negative

TPR *= tp / (tp+fn)*

FPR *= fp/(fp+tn)*

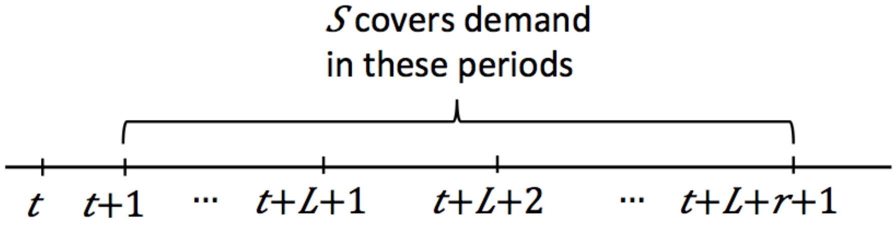
PPV *= tp/(tp+fp)* ***NPV*** *= tn/(fn+tn)*

- **TPR:** Of the total number of failures, how many were predicted?
- **FPR:** Of the total number of non-failures, how many were falsely predicted?
- **PPV:** Proportion of signals that accurately predict a failure
- **NPV:** Proportion of non-signals that accurately predict a non-failure

4. Predictive Analytics Methodology

- We use the binary classification matrix and the size of the installed base to generate a forecast
- 1. Assign signals to failures using the TPR & FPR
- 2. Adjust signals based on the PPV and NPV
- 3. Plug forecast into R, S policy

$$\mathbf{S_t} = F_{t-1,\ t+1} + F_{t,\ t+2} + z^{*}\mathrm{sqrt}(V_{t-1,\ t+1} + V_{t,\ t+2})$$



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5. Results & Data Analysis

- Each of the time-series forecasting models run 15x each
  - Find that exponential smoothing with trend model provides lower inventory while sustaining acceptable service level
  - Provides a baseline for comparison against predictive analytics model

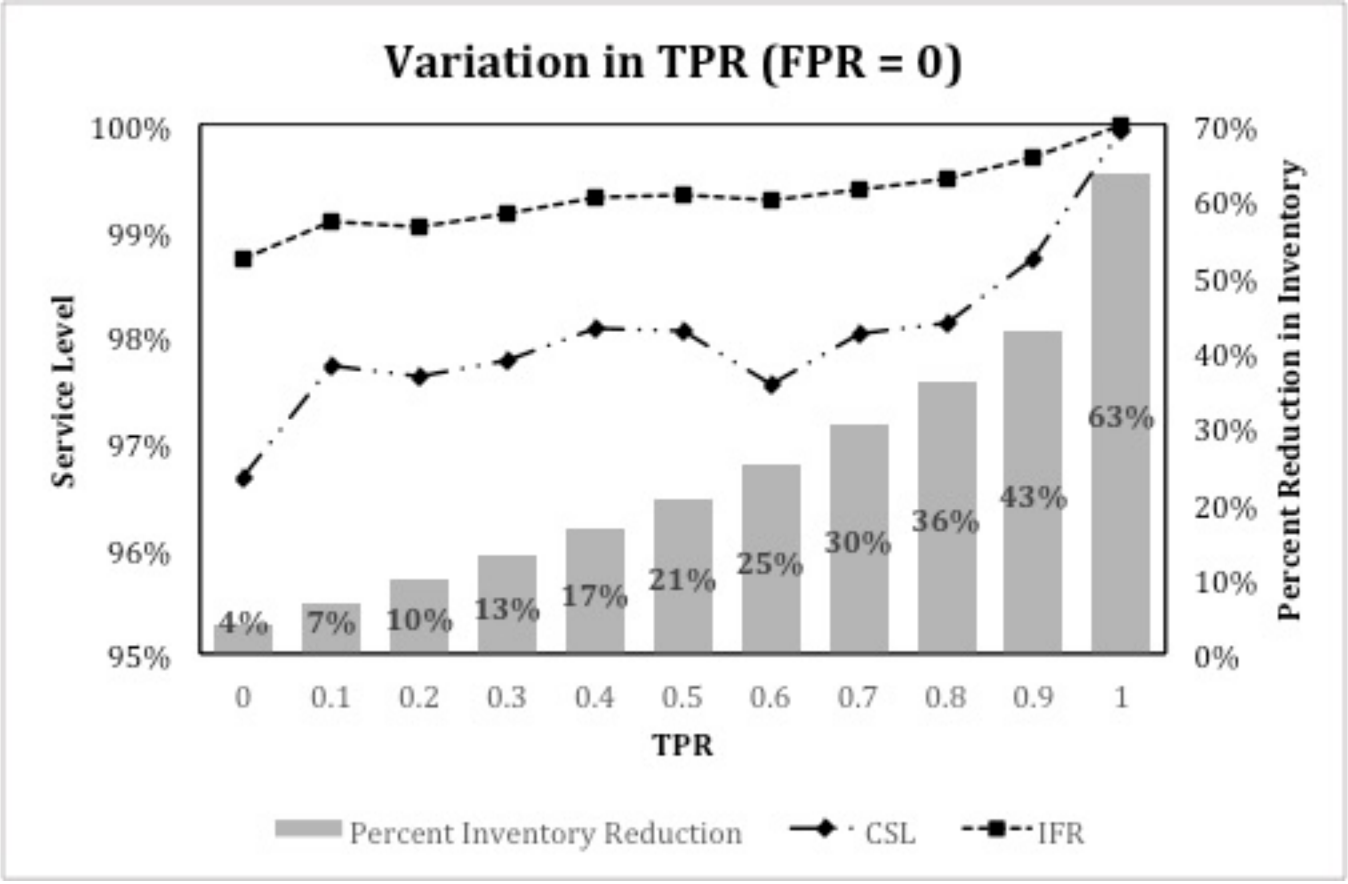
Metric	Measurement	Simple Exponential Smoothing	Simple Exponential Smoothing with Trend
Avg. Inventory	**Average**	**8.884**	**8.592**
CSL	**Average**	**96.50%**	**95.98%**

5. Results & Data Analysis

- The predictive forecast model was run 15x at each combination of the TPR and FPR in 10% increments between 0 and 1
- Allows for sensitivity analysis of varying levels of predictor accuracy
- New signals and demand statements created for each iteration of simulation in VBA

Visual Basic

5. Results & Data Analysis



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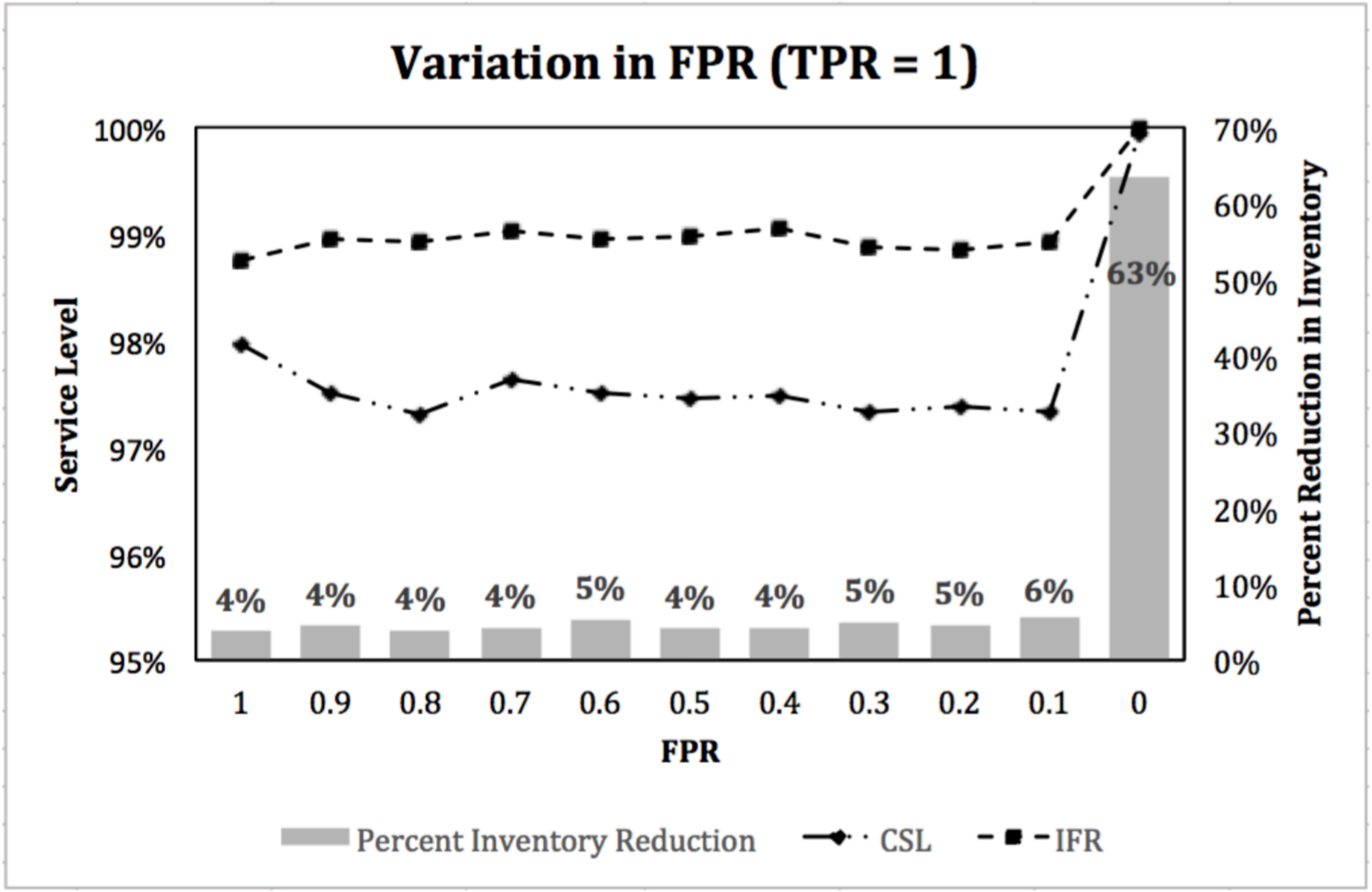
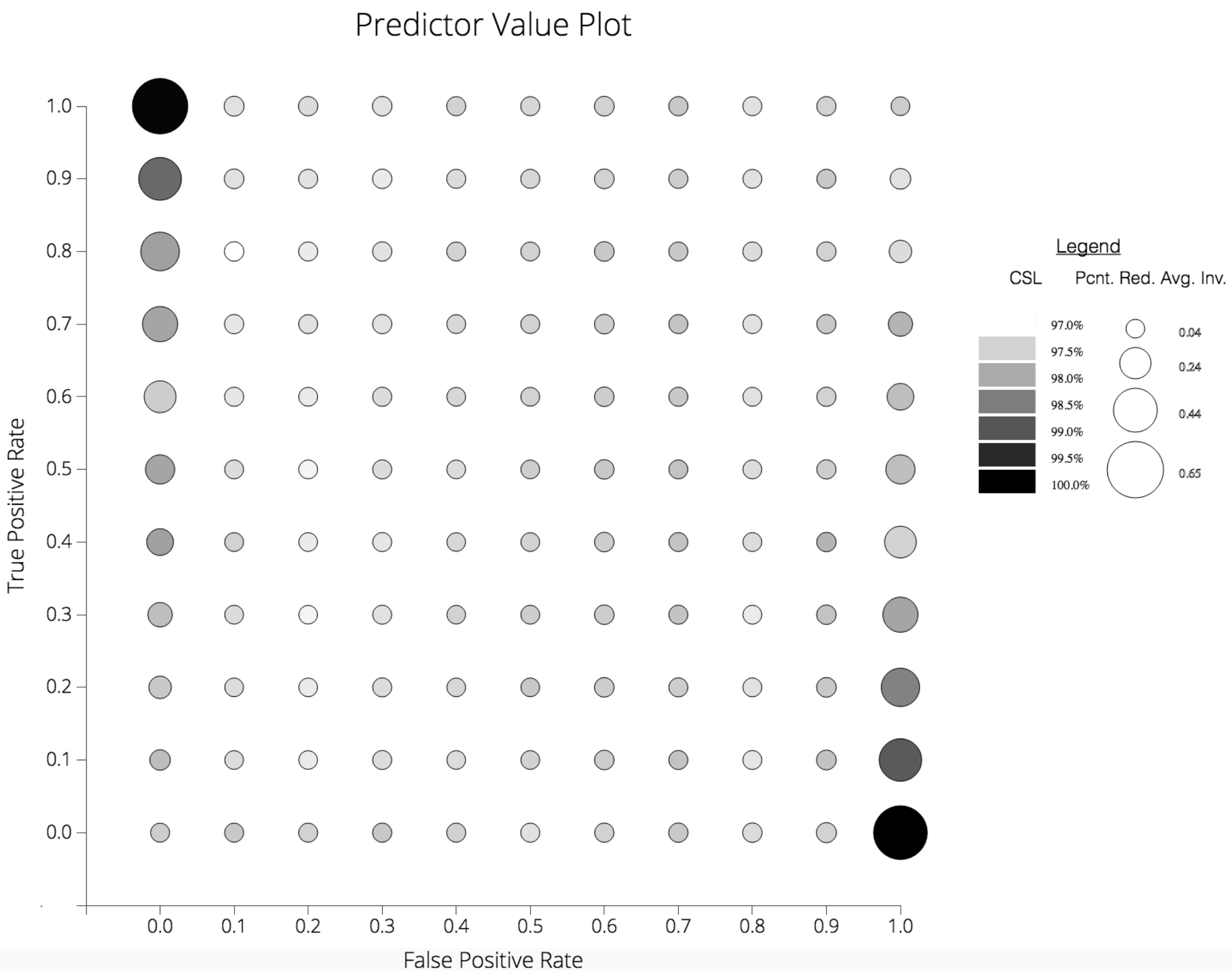


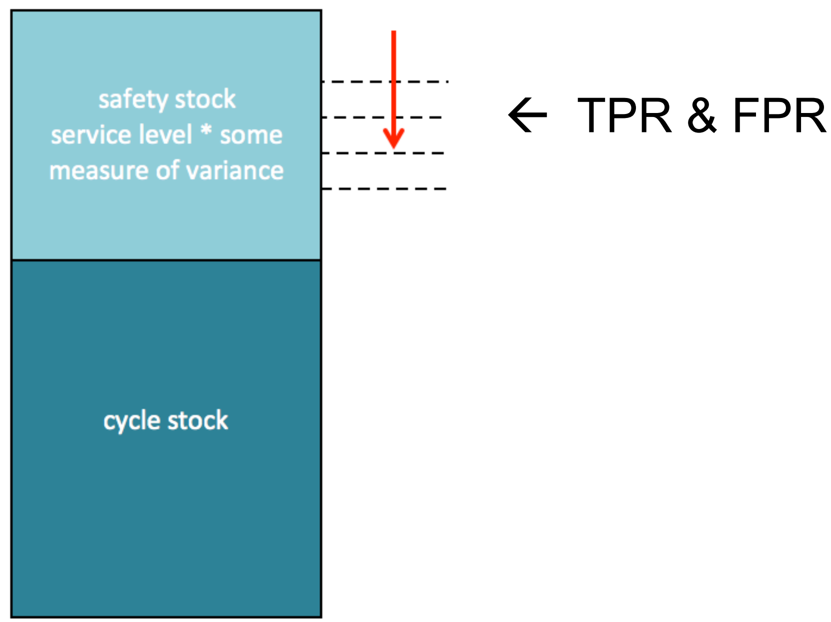
5. Results & Data Analysis

- Each of the predictive forecasting models run 15x at each unique combination of TPR and FPR, in 10% increments of each



5. Results & Data Analysis

- As confusion matrix provides more accurate results, less amount of variance in our forecast
- In turn, this drives down the necessary safety stock to reach a certain service level until reaching 0, leaving only the cycle stock and reaching the minimum possible average inventory



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Results and Data Analysis

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6. Conclusions and Implications

- Provides concrete method for meshing together predictive analytics with spare parts inventory planning

- Could :
  - Potentially represent a significant reduction in working capital for companies as they are increasingly able to squeeze inventory out of their supply chain

  - Reduce total penalty costs paid in SLA/warranty servicing as companies are able to get a better jump start on service request ahead of time

  - Potential redesign of service supply chain network to aggregate inventory across multiple local spare parts field depots & trunk stocks into more centralized locations
    - reduction in shrinkage, obsolescence and damage

Questions?