SIMULATING TOMORROW’S SUPPLY CHAIN TODAY:
CONVEYING THE VALUE OF FLEXIBILITY IN SUPPLY CHAIN DESIGN

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Flexible designs offer the best of all worlds: the opportunity to invest under favorable conditions, capturing upside gain, and the opportunity to forego additional expenditure under less favorable conditions, mitigating downside risk. Inventory stocking policies, developed to accommodate the vagaries of uncertain demand through investment in safety stock, enable companies to guarantee their customers a desired fill rate, or probability of having stock on the shelf when needed.

These stocking policies only work when they are used. If a company’s executive team does not understand the impact of variable demand upon stocking policies, believes demand to be more constant than it actually is, or doesn’t grasp the impact of multi-year procurement lead times on their company’s ability to guarantee performance metrics on a one year contract, then achieving performance goals will be difficult if not impossible.

What is needed is a visual way to convey the supply chain risk inherent in managing high dollar, low volume parts, a statistical way to formally make the point, and a financial way to communicate the financial risk. This project uses the technique of Stochastic Dynamic Forecasting to vary demand in a Line of Balance accounting worksheet used by asset managers, which then feeds a visual Line of Balance which graphs the results. A Cumulative Density function is then analyzed for two decision rules – one financial, the other operational – to conclude that analysis based on the value of the expected input is not equal to the expected value of probability-weighted input scenarios, known as Jensen’s Inequality.
The **stocking policy simulator** uses an integrated process to enable asset managers to evaluate alternate stocking policies, test their hypotheses about the best course of action, and convey their results to management.

- **Historical supply chain data** includes part number and manufacturer, demand, price, lead time, and inventory as well as historical demand data
- A **strategic inventory optimization** model determines reorder points and reorder quantities
- **Stochastic Dynamic Forecasting** predicts random future paths, based on historical data and an estimate of forecast error
- A **part is selected** from the supply chain database
- A **(s,S) Order Point, Order-Up-to-Level model** estimates fill rate based on the supply chain data, and the reorder point and reorder quantity, to validate the simulation
- Alternate stocking models, including the **Wilson Economic Order Quantity (EOQ)** model, may be compared. Asset managers may also evaluate one model
under different policies; for example, varying the review period, or adjusting price, lead time, or demand assumptions

- A Line of Balance worksheet does the accounting to estimate inventory levels over time, as demand is varied using the Stochastic Dynamic Forecast
- A Visual Line of Balance graphs the classic saw tooth inventory level, on hand, and demand curves to convey the inner workings of the model visually
- A Monte Carlo simulation model evaluates 1,000+/- scenarios, based on random demand patterns created using Stochastic Dynamic Forecasting
- Target curves of different stocking policies enable asset managers to compare policies based on fill rate or Net Present Value
- Automated hypothesis testing evaluates the null hypothesis that there is no difference between two supply chain plans

Conclusions: A program’s Fill Rate goal and desire to minimize Net Present Value (NPV) must be considered together. An appropriate decision rule is to select the stocking policy with the lowest NPV which achieves the desired Fill Rate goal.

Acquisition Policy: The preferred stocking policy should be in concert with the acquisition policy. Therefore, given an annual Government funding cycle, The Boeing Company should stock to a twelve (12) month periodic review policy. Since this requires a larger capital expenditure (CAPEX) for initial spares, due to the added twelve (12) months of pipeline inventory, the company should instead develop a financial business case for changing acquisition policy to (a) fund the “plus up” to achieve optimal stock levels, and (b) allow a funding vehicle for flexible monthly expenditures.

Long Term Contracting: As demonstrated by Jensen’s Inequality, the average of all the possible outcomes associated with uncertain parameters generally does not equal the value obtained from using the average value of the parameters. The Boeing Company should shift from basing long term contracts on average requirements, to basing requirements on an expected range of values.
**Next Steps:** This project concludes with the recommendation that this approach be extended to create a family of stocking policy simulators, electronically loaded with historical data for parts of interest, to enable asset managers to make better informed tactical decisions given demand and lead time uncertainty.

2.0 System Description

As described in The Boeing Company’s public website, the F/A-18E/F Integrated Readiness Support Teaming (FIRST) Program “is a performance-based logistics contract to provide support to the F/A-18E/F Super Hornet. The objective is to improve fleet support and aircraft readiness while reducing costs. The contract provides asset management (spares and repairs), supportability improvements, obsolescence management, technology insertion and integrated logistics support.” (The Boeing Company)

Supply chain management for the FIRST Program revolves around providing needed repair parts to from a central warehouse (known as wholesale) to customer facilities located around the world at Naval Air Stations, aircraft carriers, and depots (known as retail). Stocking policies used to manage inventories of spare parts will be evaluated under conditions of uncertain demand and acquisition policy.
Figure 2-Military Support Operations

Figure 2-Military Support Operations illustrates the sequence of unscheduled maintenance support functions. The unscheduled maintenance scenario that follows (Bradley, 2002) uses the numbering scheme shown in this figure.

(1) At the organizational level, a failure will be rectified either on or off the aircraft. On aircraft failures are usually minor and include torn seats, scratches, light bulbs, and minor adjustments. On aircraft failures which are Repaired In Place (RIP) may be inherent in the component design or induced by another failure or while another component undergoes repair; the problem may also turn out to be one which the maintenance technician Can Not Duplicate (CND). CND maintenance is also known as No Fault Found (NFF).

On aircraft maintenance also involves opening panels for access; fault isolation and detection of the failed Navy Weapons Replaceable Assembly (WRA) or Air Force Line Replaceable Unit (LRU); removal of components to facilitate other maintenance (FOM); removing and replacing (R&R) the failed WRA/LRU with a spare; testing the repair; and replacing all other components and panels. The failed WRA/LRU is then sent to the intermediate level for off aircraft maintenance.
The squadron performs organizational level maintenance with its assigned equipment. Support operations include inspecting; servicing; lubricating; adjusting; and replacing parts, minor assemblies and subassemblies.

(2) At the intermediate level, the maintenance technician checks the repair level designation of the removed WRA/LRU. The most economical repair level for each WRA/LRU was determined in the design phase of aircraft development using a Repair Level Analysis (RLA) model. It is determined whether the WRA/LRU is repairable, should be condemned and scrapped, whether the technician Cannot Duplicate (CND) the problem on a test station, or whether the part is Beyond Capability of Maintenance (BCM) in the Navy, or Not Repairable This Station (NRTS) in the Air Force, and should be sent to a depot for repair. The WRA/LRU may be further broken into subassemblies known as Navy Shop Replaceable Assemblies (SRAs) or Air Force Shop Replaceable Units (SRUs), such as throwaway avionics circuit cards. These are sometime broken further into Navy Sub SRAs (SSRAs) and Air Force Sub SRUs (SSRUs). Once repaired, the spare is either installed in an aircraft that is Awaiting Parts (AWP) or is sent to supply.

Intermediate level maintenance is performed at the base shop, which directly supports the using organization. Support operations include calibrating, repairing, or replacing damaged or unserviceable parts, components, or assemblies.

(3) At the depot level the WRA/LRU or SRA/SRU is either repaired or condemned. If condemned, a new component is procured from the vendor. The repaired item is then sent to intermediate level supply. In an O to OEM concept, the item may also be shipped directly to the vendor (Boeing) for repair or replacement.

Depot level maintenance provides more extensive shop facilities and equipment and personnel with higher technical skill than is available at the organizational or intermediate levels.
(4) The supply support system provides spare WRAs/LRUs. For Boeing’s F/A-18E/F program, this is the Boeing warehouse operated by North Carolina based supply chain management company New Breed Logistics Inc.

(5) When the WRA/LRU has been replaced and all the gripes have been worked off, the aircraft is upgraded to Fully Mission Capable (FMC).

3.0 Sources of Uncertainty

Supply chain uncertainty comes from multiple sources. This project will consider demand variability and order quantity variability together as variability of monthly demand. Acquisition policy will also be considered as review policy; that is, whether orders are placed monthly, quarterly, or annually. Other sources of uncertainty, which are candidates for inclusion in future development spirals, are captured for completeness.

Exogenous uncertainties, which are not influenced by managerial decisions, include:

- **Demand Variability** – How often aircraft parts require maintenance
- **Procurement Lead Time Variability** – The time vendors require to fabricate a new part
- **Order Quantity Variability** – How many parts retail (Naval Air Stations, carriers, or depots) orders from wholesale (the New Breed warehouse)
- **Condemnation rate variability** – Whether repairable parts can be fixed to a Ready For Issue (RFI) condition, or are discarded as Beyond Economical Repair (BER).

These uncertainties are path independent, because supply chain issues with one part do not impact other parts.

Endogenous uncertainties, which are influenced by managerial decisions, include:
• **Stocking Policy**—The Reorder Point and Reorder Quantity may be set by a number of different models. Safety stock may be added as a buffer against uncertainty in order to achieve a desired level or performance, such as fill rate.

• **Acquisition Policy** – Whether funding contracts are annual or quarterly, and whether the contracts allocate budget for a fixed quantity of specific part numbers, or general budget to be used flexibly based on random demand.

• **Repair Turnaround Time Variability** – Repair turnaround time is a function of the authorized budget, because in a tight economy not all failed parts are funded for repair. Further, the fill rate goal for consumable piece parts impacts the ability to effect repairs at the depot using piece parts from on-hand stock.

In the special case of depot level repair of components, these uncertainties are **not path independent**, because shortages of “child” piece parts impact the ability to repair the “parent” component, which extends the repair turnaround time of the component, causing a ripple effect in the supply chain. Further, depots will often fabricate parts internally, or at local machine shops, or buy consumable parts outside of formal supply channels, skewing the apparent distribution of demand for child piece parts which are in short supply.

### 3.1 Quantifying variability

a. **Variability of Monthly Demand** - Demand variability and order quantity variability are analyzed as variability of monthly demand, which will be demonstrated through creation of “a dynamic forecasting model, that is, a spreadsheet module that produces a range of forecasts drawn from a sensible distribution.” (de Neufville & Scholtes, 2011, pp. 94-96) This will be done by creating error paths, as described in de Neufville Chapter 4, and adding these randomly to a level projection using Boeing’s traditional forecasting process, that is, Simple Exponential Smoothing. The result will be the series of potential forecasts depicted below: (de Neufville & Scholtes, 2011, p. 96)
b. **Demand Variability** - The distribution of demand for spares parts is traditionally modeled using a Poisson distribution. The Poisson is a discrete probability distribution that is commonly used to determine the number of occurrences of a part failing within an interval of time. The most common techniques for forecasting low and intermittent demand are Simple Exponential Smoothing (SES) (Willemain, 1994) and Croston’s Method, which considers both the frequency between orders and the order size (Croston, 1972). Since SES is commonly used in the aircraft industry, this technique was utilized using the industry standard 10% smoothing constant to create the initial demand forecast based upon five years of historical demand data.

c. **Demand Variability (Spiral 2)** - A more complex extension, out of scope of this project, would also incorporate the binomial distribution if variance is < 0.95 * mean, the Poison if the variance to mean ratio is between 0.95 and 1.05 inclusive, and the negative binomial distribution if the variance > 1.05 * mean. "The negative binomial distribution… can be used as an alternative to the Poisson distribution. It is especially useful for discrete data over an unbounded positive range whose sample variance exceeds the sample mean. In such cases, the observations are overdispersed with respect to a Poisson distribution, for which the mean is equal to the variance. Hence a Poisson distribution is not an appropriate model. Since the negative binomial distribution has one more parameter than the Poisson, the second parameter
can be used to adjust the variance independently of the mean.” (Negative Binomial, 2011)

d. **Order Quantity Variability** – Order quantity varies significantly on a part by part basis, and has traditionally been modeled using an empirical distribution. Since demand is divided into monthly time buckets using this formulation of Stochastic Dynamic Forecasting, the distinction between order frequency and order quantity goes away.

![Empirical Order Quantity Distribution](image)

Figure 4: An empirical distribution was first proposed for quantifying variability of order quantity, but later eliminated in favor of Stochastic Dynamic Forecasting of demand in monthly time periods.

e. **Procurement Lead Time (PLT) Variability** - While procurement lead time also varies on a part by part basis, this variability will be excluded from the current analysis. Since orders tend to be relatively infrequent, an empirical distribution based upon the frequency of observed lead times would be appropriate for modeling PLT variability.
4.0 Fixed and Flexible Designs

An Excel based simulation model was created as a concept demonstrator, and loaded with actual supply chain data for six representative consumable parts used in maintenance of the F/A-18E/F Super Hornet Naval attack fighter, which is manufactured by The Boeing Company in St. Louis, MO. The exploration of uncertainty has been narrowed to four decision rules which vary over time, specifically, four alternate stocking policies which The Boeing Company has used in the past. This project demonstrates that a simulator could be developed as an on-line decision support tool, allowing asset managers to make operational day-to-day decisions concerning individual parts of interest, in concert with the optimized goals of a Commercial Off The Shelf (COTS) inventory optimization model. The value is in demonstrating the stochastic nature of inventory management, and in quickly evaluating alternate stocking policies. Another value is in allowing asset managers to update stocking policies based on additional data, such as revised demand, pricing, or lead time data, without having to wait for a monthly or quarterly run of the strategic inventory optimization model.

Three specific cases will be evaluated using simulation:

a. **Flexible Designs**: Evaluate four stocking policies

b. **Acquisition Policy**: Evaluation continuous vs. periodic review policies

c. **Jensen’s Inequality**: Evaluate fixed design (constant demand) vs. flexible design (variable demand)

4.1 Stocking Policy Evaluation

4.1.1 Fixed case

The fixed case for the stocking policy evaluation is representative of the current procurement contracts for spare parts in The Boeing Company’s Boeing Defense, Space, & Security (BDS) business unit.
**Fixed Quantity Long Term Contact** – This option will be modeled by assuming constant demand, which is the underlying assumption behind long term contracts which are written based on average annual demand.

### 4.1.2 Flexible designs

The flexible cases are designed to highlight whether a flexible approach to contracting and stocking policy would offer business value. Four flexible approaches were modeled, although this paper will focus on evaluating stock level recommendations from the SPO Strategy model. The fifth model, an Order-Point, Order-up-to-Level Model, was designed to validate the simulation by reverse engineering the expected fill rate of a given stocking policy.

**a. SPO Strategy by MCA Solutions** – This is an (s,S), or (Order-Point, Order-up-to-Level) inventory model, in which the objective function is to minimize the cost of initial inventory for a given fill rate constraint. The most commonly used inventory optimization model at The Boeing Company, it is also the most complex and therefore least well understood.

**b. VMetricXL by TFD Group/Systems Exchange** - This desktop inventory optimization model is often used on proposals by The Boeing Company. Based on discussions with the vendor, the stocking policy was implemented in Excel, using the Expected Backorder (EBO) target from the inventory optimization to set safety stock. The EBO target can be used to effectively mimic the parameters of the SPO Strategy model, enabling comparisons between the two models on a part-by-part basis. This is also an (s,S), or (OrderPoint, Order-up-to-Level) inventory model.

**c. The Wilson Economic Order Quantity (EOQ) Model** - When run in its original form, this model assumes that an order arrives exactly when inventory is depleted to zero. This is useful, because the safety stock may be calculated as the difference between the reorder point of any other model, and the Wilson EOQ
reorder point. This model was implemented in the VMXL worksheet depicted below.

![Image of VMXL worksheet](image)

Figure 5- Economic Order Quantity Model developed to investigate the VMetric-XLReorder Point and Reorder Quantity calculations.

d. **Chief of Naval Aviation for Training (CNATRA)** - This heuristic for consumable parts has been used on the T45TS Navy Trainer in Kingsville, Texas. This is a simple stocking policy which holds a certain number of months of inventory. This model was also implemented in the VMXL worksheet.

e. **Order-Point, Order-up-to-Level Model** – A Cycle Service Level (CSL) model known as P1 (Silver, Pyke, & Peterson, 1998) was implemented in Excel. An innovation added to this model determines fill rate and expected backorders per period (EBOs)
when the Reorder Point (ROP) and Reorder Quantity (ROQ) are known. The CSL model was modified to estimate fill rate and EBOs using a technique known as the normal loss function (Metin, 1995) and (Tibben-Lembke, 2009).

Figure 6—Economic Order Quantity Model developed to explore the SPO Strategy and VMetric-XL Fill Rate and Expected Backorder Calculations.
4.2 Acquisition Policy Evaluation

Acquisition policy will be modeled by assuming that an inventory optimization model has been run using a continuous review policy model, but that funding cycles are annual resulting in a de facto periodic review policy. This occurs when an annual Government budgeting process specifies funding by part number and quantity, which would necessitate a Periodic Review Model, but the contractor uses a traditional Order-Point, Order-up-to-Level Model. Target Curves of the resulting fill rate from an (s,S) stocking policy versus an (R, s, S) stocking policy will be evaluated. Although not considered in this paper, as a further refinement stockout cost could be included as the theoretical value of lost performance incentive, known as award fee.

4.2.1 Fixed case

The fixed case for the acquisition policy evaluation will be modeled by simulating an (s,S) model under periodic review conditions.

**Periodic-Review, Order-Point, Order-Up-to-Level Model (R, s, S)** - By not including annual funding cycles into the spares calculations, the contractor may be under sparing programs. With a periodic review model, the appropriate review lead time would be added to the calculation of lead time: for an annual funding cycle, 12 months, or for a quarterly funding cycle, 3 months.

4.2.2 Flexible case

The flexible case will modeled by evaluating an (s,S) model under monthly review conditions.

**Order-Point, Order-up-to-Level Model (s,S)** - When inventory drops to or below reorder point, an order is placed up to target stock level.
5.0 Selection of Analysis Method

The classic methods for evaluating uncertainty in Real Options are Decision Analysis, the Lattice model, and Simulation, with simulation being the appropriate approach.

a. **Decision Analysis** - A decision tree is a graphical tool for modeling sequential decisions under uncertainty. Elements include decision nodes (square indicating possible actions at a choice point), uncertainty notes (circle showing possible outcomes with probabilities), and outcome nodes (triangle with probability and expected value). Using decision analysis would require making a decision at each review period of the inventory analysis, including complex decision rules that vary by scenario. A decision analysis would rapidly become intractable.

b. **Lattice** - A recombinant lattice is a way of representing the evolution of uncertainty, constructed in a way that possible outcomes coincide (recombine) in order to reduce the number of possible outcomes to a linear function of the number of stages. Lattices can model uncertain stochastic processes that do not change over time (stationary) and that are not affected by individual actions (exogenous and path independent). This project requires complex decision rules based on inventory models, and requires that these inventory models be recalculated annually. Since there are multiple flexibilities involved, a lattice cannot be used.

c. **Simulation** - Simulation replicates outcomes of an uncertain process. It provides a way to describe what may occur over a range of scenarios. It allows decision rules. It can use a variety of distributions (regular or irregular, continuous or not). Advantages include that simulation can model multiple decisions, can handle many periods, and is relatively easy to explain.

d. **Justification of Analysis Method** - Simulation is the classic approach to modeling uncertainty in aviation spare parts, is the appropriate solution for modeling complex decision rules, and can be explained to a non-technical person in the supply chain field. Further, developing a flexible simulation will allow a
single model to simulate inventory policies for different unique parts, creating significant Economies of Scale (EoS).

6.0 Simulation Setup

In order to both evaluate and explain stocking policies, and to convey the nature of a supply chain simulation to non-technical managers, an accounting model known as a Line of Balance was visualized using graphics to create a Visual Line of Balance. Each time the What-If? Button is pressed on the spreadsheet, a different Stochastic Dynamic Forecast is generated, a different set of stocking decisions are made based upon the stocking policy and the flexibilities selected. The decisions are evaluated on a monthly basis for a continuous review policy, or a periodically for a periodic review policy. A cash flow model calculates the Net Present Value of the Total Relevant Costs based on the actual monthly inventory positions. A fill rate model calculates the average fill rate, again based on the actually monthly inventory positions. Finally, the Target Curve and Value and Risk and Gain (VARG) are determined for both NPV and Fill Rate.

The Executive Summary contains an overview of the stocking policy simulator.

6.1 Ground Rules and Assumptions (GR&A)

The model for the four decision rules (stocking policies) was loaded with supply chain data for six (6) aviation parts of interest, for which historical demand data and current supply chain data existed.
<table>
<thead>
<tr>
<th>Part Number</th>
<th>Cage</th>
<th>Part Name</th>
<th>Annual Demand</th>
<th>PLT</th>
<th>Order Cost</th>
<th>Holding Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE12435-408-303</td>
<td>68999</td>
<td>CABLE ASSEMBLY, RADI</td>
<td>54.91</td>
<td>379</td>
<td>500</td>
<td>22%</td>
</tr>
<tr>
<td>5911804-1</td>
<td>99167</td>
<td>BOOT, AIRCRAFT, MATER</td>
<td>76.84</td>
<td>456</td>
<td>50</td>
<td>22%</td>
</tr>
<tr>
<td>74A231636-1003</td>
<td>76301</td>
<td>CONNECTING LINK, RIG</td>
<td>84.82</td>
<td>554</td>
<td>250</td>
<td>22%</td>
</tr>
<tr>
<td>74A343517-2006</td>
<td>76301</td>
<td>FAIRING, AIRCRAFT</td>
<td>57.48</td>
<td>781</td>
<td>250</td>
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</tr>
<tr>
<td>M83461~1-011</td>
<td>81349</td>
<td>O-RING</td>
<td>123.25</td>
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<td>76301</td>
<td>PIN, STRAIGHT, HEADED</td>
<td>207.46</td>
<td>150</td>
<td>50</td>
<td>22%</td>
</tr>
</tbody>
</table>

Table 1 - Representative parts used to evaluate stocking policies

The model is operated by entering the part number (Row 5, labeled Data_Part_No and flagged with <= ENTER PART NUMBER). The part number must correspond to a worksheet loaded with supply chain data. Two models may be selected for comparison, either EOQ (loaded with data from SPO Strategy), VMXL (loaded with data from VMetric-XL), the WILSON EOQ model, or the CNATRA heuristic (Row 14, labeled Data_Model). Clicking the What-If? Button then loads the Data worksheet, which provides data to the other modules of the simulation.
Table 2-Loading supply chain data from into the "Data Worksheet" populates the enter suite of decision support simulation tools.

The model incorporates a number of additional features, such as allowing known "over and above" requirements to be specified as Programmed Demand. This is common for a one time buy to cover a retrofit program, or to cover a planned series of depot overhauls where the purchase is non-recurring and for which historical data does not exist. The model considers the on-hand and backorder inventory balances, and also incorporates due-in orders from the inventory management system, by order date and requisition quantity. In this manner, the model is able to accurately simulate tomorrow's supply chain performance using an exact snapshot of today's parameters.
6.2 Decision Rules

The decision rules for stocking policy models are surprisingly complex. Ostensibly, the model must simply evaluate the Inventory Position, placing an order for replenishment stock which will arrive Procurement Lead Time (PLT) in the future. Accounting for the sequence of orders placed monthly, with inventory arriving lead time away, is a fairly complex exercise in accounting. Further, numerous business rules need to be evaluated, such as whether to order up to Target Stock Level, or to simply place an order in the Reorder Quantity when stock drops below Reorder Point. These decision rules are implemented as user selectable flags, which are shown in the header of the attached “Line of Balance” worksheet.

Figure 7-An accounting spreadsheet known as a Line of Balance is used to evaluate part requirements over time. This model has been modified to incorporate uncertain demand using a stochastic dynamic forecasting model.

The companion Visual Line of Balance worksheet shows the inventory position in dashed blue, the on-hand inventory in yellow, back order conditions in yellow with black dashes,
and monthly demand in green. Pressing the What-If? Button updates the graph with a different version of how a five year period might play out. The value of this worksheet is in quickly conveying exactly what the simulation model does: it evaluates stocking policies by rolling the dice to determine whether one is going to run out of parts, and if so for how long, under a variety of different scenarios.

Table 3-The Visual Line of Balance shows the inventory position in dashed blue, the on-hand inventory in yellow, back order conditions in yellow with black dashes, and monthly demand in green. The What-If? Button updates the graph with a different scenario.
6.3 When Flexibility is Exercised

In order to incorporate variability of monthly demand in the decision making process, a user selectable flag specifies whether to assume constant demand, or to use variable demand generated by the Stochastic Dynamic Forecast.

In order to incorporate different acquisition policies, another flag specifies the number of periods between resupply, which may be any number of periods (months) one or greater. This is equivalent to selecting the funding profile, whether monthly, quarterly, or annually.

Inventory position is defined as on-hand + due-in – backorders. When inventory position dips to or below reorder point, and order is placed in either reorder quantity or up to stock level depending on the desired policy. The parameters of the stocking policy (ROP & ROQ) are determined by one of the four stocking models described earlier.

By running any user selectable number of simulations, a Target Curve is generated to evaluate any two combinations of stocking policy and acquisition policy, and considering a number of different settings. This allows decision makes to understand the impact of different stocking policy options, and allows asset managers to evaluate the impact of different settings in the SPO Strategy and VMetric-XL global inventory optimization models. Further, this provides Boeing management with a way to communicate the value of moving away from an annual acquisition process to their Government customers.

6.4 Simulation Validation

Part Number 5911804-1, CAGE 99167, Nomenclature BOOT, AIRCRAFT, MATER was simulated for 1,000 iterations with a ROP of 118, ROQ of 21, and Stock Level of 139. Variable demand was simulated using Stochastic Dynamic Forecasting.
The stocking policy simulation was validated by comparing the simulated results to the predicted results from a model of specified fraction (known as P2) of demand which is routinely satisfied from the shelf, or fill rate (Silver, Pyke, & Peterson, 1998). Based upon this model, the anticipated fill rate should be 88%.

<table>
<thead>
<tr>
<th>Performance Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cycle Service Level (CSL) – Silver, Pyke and Peterson (SPP) calls this P1</td>
</tr>
</tbody>
</table>

\[ \sigma_L = \text{RMSE} \]

\[ X_L = \text{(as Leadtime)} \]

\[ s = xL + k\sigma_L = \text{Reorder} \]

<table>
<thead>
<tr>
<th>Leadtime (months)</th>
<th>Annual Demand</th>
<th>Leadtime Demand</th>
<th>k = Safety Stock factor</th>
<th>Standard Deviation</th>
<th>k\sigma_L = Safety Stock</th>
<th>Reorder Point</th>
</tr>
</thead>
<tbody>
<tr>
<td>15.00</td>
<td>76.84</td>
<td>96</td>
<td>0.89</td>
<td>25</td>
<td>21.95</td>
<td>118</td>
</tr>
</tbody>
</table>

Find...

Safety stock and reorder point, s, for the following cycle service levels:

\[ \text{CSL}=0.814 \]

\[ 81.40\% \]

\[ 0.89 \]

\[ 22 \]

\[ 118 \]

\[ 21 \]

<table>
<thead>
<tr>
<th>CSL=NORMS DIST(k)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_2 = 1 - G_u(k) )</td>
</tr>
<tr>
<td>( \sigma_L / Q^* )</td>
</tr>
<tr>
<td>( P_1 = \text{CSL} )</td>
</tr>
<tr>
<td>( P_2 = \text{Fill Rate} )</td>
</tr>
<tr>
<td>( k )</td>
</tr>
<tr>
<td>( f_u(k) )</td>
</tr>
<tr>
<td>( p_{u&gt;}(k) )</td>
</tr>
</tbody>
</table>

Calculation from ROP & ROQ

\[ 81\% \]

\[ 88\% \]

\[ 0.8926 \]

\[ 0.2678 \]

\[ 0.1860 \]

Table 4-Estimate of fraction of demand to be satisfied routinely from the shelf (Fill Rate) based upon ROP & ROQ.

The mean fill rate of the simulation was 92.7%, as shown in the table below.
A hypothesis was formulated that the simulated mean was greater than or equal to the calculated fill rate of 88%. A z-test for the hypothesis of the mean was performed to answer the question of whether this is a good model. At a 95% level of confidence, there was no reason to reject the null hypothesis.

Table 5-Summary results for fill rate simulation of the SPO Strategy stock levels

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>92.7%</td>
</tr>
<tr>
<td>Max</td>
<td>100.0%</td>
</tr>
<tr>
<td>Min</td>
<td>47.2%</td>
</tr>
<tr>
<td>StdDev</td>
<td>10.4%</td>
</tr>
<tr>
<td>Count</td>
<td>1,000</td>
</tr>
</tbody>
</table>

Table 6-A z-Test for the Hypothesis of the Mean, when Standard Deviation is known, shows no reason to reject the null hypothesis that the mean is greater than or equal to 88% fill rate.
Therefore, we can conclude that the simulation model is a good representation of fill rate for this part. We can also infer that the simulation would be equally good at modeling parts with other supply chain parameters.

7.0 Stochastic Dynamic Forecasting

All current strategic inventory optimization models incorporate variability as a ratio between the variance of the part within lead time, and the mean of the variance. Existing spreadsheet analysis assumes constant demand. But what if the demand is truly variable, as data of historical demands indicates? To incorporate variability into this model, a stochastic dynamic forecasting model was developed using five years of historical demand data. This particular example shows part number 5911804-1, named “Boot, Aircraft, Mater” and made for the F/A-18E/F Navy attack fighter by Sunstrand Aerospace/Hamilton Sunstrand Corporation. The part goes into a gearbox assembly.

Figure 8-The Stochastic Dynamic Forecasting process creates an additive forecasting model using regression of the log-transformed historical data and an estimate of the random error distribution.
Stochastic Dynamic Forecasting is a way to represent the uncertainties around a demand forecast in an intuitive and graphical manner. Further, the nature of the resulting equation, which estimates the next period based upon the previous period plus a random error, makes this process amenable to simulation. The process involves these steps:

- **Historical Data**, such as requisitions for spare parts including an order date, part number, and quantity, is aggregated into periodic time buckets, usually monthly.
- **Simple Exponential Smoothing (SES)**, in this case, is used to explain the difference between Stochastic Dynamic Forecasting and traditional demand forecasting. The SES estimate also serves as the initial estimate X(t).
- The **Periodic Data Series for Consecutive Periods** is graphed to visualize the historical data.
- An Ordinary Least Squares (OLS) **regression model** of the historical data is created. Often, a scatter plot shows irregular behavior. In this case, many points cluster at the lower end of the regression line, and the variation parallel the y-axis is not uniform. This indicates heteroscedasticity, or different variation.
- A **log-transformation** of the historical data dampens the greater effect of higher values.
- A **Probability Density Function (PDF) of the error** vs. the expected error for a normal distribution suggests that the resulting model is reasonable.
- **Histograms** of the Stochastic Dynamic Forecast error, and the expected error for a normal distribution, allow a visual comparison.
- The data for these distributions are compared using a **Chi-Square Goodness of Fit test** for the desired level of confidence to test the hypothesis that the error is normally distributed.
- The **parameters of the additive forecasting model** are a (slope), b (y-intercept), and (t) (independent normal error). The SES estimate of the next period’s demand is used as the seed X(t) for the Stochastic Dynamic Forecast.
- By selecting the error in each period as an independent normal error with a mean zero and standard deviation (t), the **additive forecasting model** is easily implemented for spreadsheet analysis.
The stochastic dynamic forecasting model was developed in Excel, and calibrated using historical demand data (de Neufville & Scholtes, 2011), (Lee Y. S., 2009) and (Lee, 2009).

A forecast model was generated with the following parameters, where \( t \) is a random shock variable with a normal distribution with mean zero and standard deviation 0.3796.
\[ X(t) = X(t-1)^a \exp(b + (t)) \]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.2603 SLOPE Dynamic_a</td>
</tr>
<tr>
<td>b</td>
<td>1.9788 INTERCEPT Dynamic_b</td>
</tr>
<tr>
<td>(t)</td>
<td>0.3796 STD DEV OF Dynamic_E</td>
</tr>
<tr>
<td>SES Forecast</td>
<td>8.99 Dynamic_SES</td>
</tr>
</tbody>
</table>

Figure 11-The parameters for Stochastic Dynamic Forecasting, based analysis of historical data for part number 5911804-1, an Boot, Aircraft, Mater.

The historical demand data is plotted over time, showing the variability of demand on a month to month basis.

![Figure 12-Monthly demand data for 60 consecutive periods. Notice the preponderance of months in which zero demand occurred.](image)

A regression line is fit to the scatter plotted data for \( x(t) \) on the vertical axis against \( X(t-1) \) on the horizontal axis. This creates an equation for an additive forecasting model, in which the next period’s demand is a forecast of the previous period. However, this plot shows many points non-uniformly distributed on either side of the line, indicating heteroscedasticity, or different variations around the mean.
Performing a log transformation of the model dampens the impact of the greater values, correcting for heteroscedasticity. This results in a regression model with a more balanced spread.

The Probability Density Function (PDF) of the regression errors, in blue, were compared to the expected errors for a normal distribution, in red. The regression errors appear to be normally distributed.
A histogram of forecast error was created, showing the frequency of observation on the vertical axis, compared to the number of observations on the horizontal axis.

For comparison, a histogram of the number of observations which would be expected if the forecast error was normally distributed was created.
A Chi-Square goodness of fit test was used to determine whether it is plausible to assume that monthly demand for this part is normally distributed. With a Chi-Square test, the p-value is the smallest level of alpha (level of significance) such that we would reject the Null Hypothesis with our current set of data. At a 95% level of confidence, alpha = 5%. Since alpha = 0.05 < (less than) p-value = 0.0830, we find insufficient evidence to reject the null hypothesis that the monthly forecast error of Part No. 5911804-1 is normally distributed.

One result of developing a forecast using monthly time buckets, in conjunction with the stochastic dynamic forecasting process, is that it will not be necessary to develop the empirical order quantity distribution originally envisioned. The random, often large, swings in the dynamic process capture the significant swings seen in order quantity when reviewing the historical demand data.

As noted in the literature, calibrating a forecasting model to the same data used to create it is statistically flawed. A better practice would be to use a jack-knifed dataset, in which earlier data used to calibrate the model was used to estimate later data to test consistency (de Neufville & Scholtes, 2011).
One issue that arises with Stochastic Dynamic Forecasting is that periods with zero demand are not allowed, as the natural logarithm of zero is undefined. As a naïve workaround, an arbitrary “offset” was added to the demand for each period. This had the impact of transforming the y-axis of the regression line upwards by the arbitrary offset. After the Stochastic Dynamic Forecast was created, the estimate was shifted down by the offset. If the result was negative, the result was rounded up to zero. While this heuristic arguably introduces a bias into the results, it is expedient.

In correspondence on the subject of periods with zero demand with Prof. Stefan Scholtes of the Judge Business School, University of Cambridge, Prof. Scholtes writes “On the notion of zero demand: Log-transforms make only sense when the probability of zero demand is negligible, which is not the case in your example. You need another model if you have zero demands. The correct model for this situation is Poisson Regression (you can look this up in any statistics textbook). You may well have so-called "zero-inflated" data, so will have to use an appropriately adapted Poisson model. The zero-inflation (i.e. more zeros than you would expect from a standard Poisson model) could be due to stock-outs (when sales (which is what you measure) was zero it is possible that there was no demand or that there was demand but no stock).” (Scholtes, 2011)

**Next steps:** Zero-Inflated Poisson (ZIP) Regression was investigated. There are a number of on-line sources of information on the subject, although specialist statistics packages are required for analysis. Because the majority of spares demand data follows a Poisson distribution, and contains zeroes, this is an excellent subject for further research and a technical paper. Further, the demand data used for this analysis comes from the F/A-18E/F Navy fighter/attack aircraft, and represents wholesale demand (requisitions for new parts to The Boeing Company) from the retail fleet (Naval Air Stations, aircraft carriers, and maintenance depots). Presumably retail is ordering in their own Economic Order Quantity (EOQ), often in fiscal budgeting cycles, which would lead to lumpy demand and the excessive zeros suggested by Prof. Scholtes.
8.0 Evaluation

Two measures of merit, one financial and one operational, were used to quantify differences in stocking policies. These criteria are:

a. **Net Present Value (NPV) of Total Relevant Cost** – The NPV, or net present value, is the discounted value of future cash flows, at an appropriate discount rate. The total cost equation is:

\[
TC = A \left( \frac{D}{Q} \right) + vr \left( \frac{Q}{2} + k\sigma_i \right)
\]

i. \( Q \) = order quantity (units)
ii. \( A \) = fixed ordering cost ($)
iii. \( v \) = unit cost ($ / unit)
iv. \( r \) = carrying cost ($ / $ / unit time)
v. \( D \) = average demand (units / unit time)
vi. \( L \) = order lead time
vii. \( k \) = safety stock factor

Note that this equation only holds under average, or steady state, conditions. The simulation model will use the same variables to calculate order cost based upon the actual number of simulated orders placed each year, and holding cost based upon the average monthly inventory on hand.

b. **Fill Rate** (Fraction of Demand to be Satisfied Routinely from the Shelf) – “The fraction of customer demand that is met without backorders or lost sales.” (Silver, Pyke, & Peterson, 1998, p. 245)

8.1 Flexible Designs (Evaluate stocking policies)

Four stocking policies, which have been used at The Boeing Company at different times, were evaluated. These are:

a. **SPO Strategy** – An inventory optimization model used on executing programs
b. **VMetric-XL** – An inventory optimization model used in proposals
c. **Wilson EOQ** – The classic Economic Order Quantity model
d. CNATRA – A heuristic for setting ROQ and ROQ based upon lead time and demand

The VMetric-XL model was normalized to the same backorder target as SPO Strategy. Note that the Stock Levels between the two are almost identical. Interestingly, VMetric-XL contains a business rule to order at least six months of inventory, which is added to the ROQ. VMetric-XL also adds the safety stock to the ROP, which covers variability in demand which occurs in the procurement lead time of the part. For next steps, it is recommended that the use calculations of expected backorder target be reviewed, to validate the methodology for converting between SPO Strategy and VMetric-XL stocking policies. The goal here is to evaluate stocking policies at the part level, given that an inventory optimization run has been conducted, not to compare or validate the inventory optimization logic of each of these models. Of course, both models may also be run independently, and their separate stocking recommendations compared in the Stocking Policy Simulator.

These stocking policies were evaluated for Part Number 5911804-1, CAGE 99167, Nomenclature BOOT, AIRCRAFT, MATER was modeled. The Contractor and Government Entity (CAGE) Code identifies the part manufacturer. The stocking level recommendations of each policy are summarized below.

<table>
<thead>
<tr>
<th></th>
<th>SPO Strategy</th>
<th>VMetric-XL</th>
<th>WILSON EOQ</th>
<th>CNATRA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ROQ</strong></td>
<td>21</td>
<td>39</td>
<td>21</td>
<td>123</td>
</tr>
<tr>
<td><strong>ROP</strong></td>
<td>118</td>
<td>98</td>
<td>98</td>
<td>104</td>
</tr>
<tr>
<td><strong>Stock Level</strong></td>
<td>139</td>
<td>137</td>
<td>119</td>
<td>227</td>
</tr>
<tr>
<td><strong>Safety Stock</strong></td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 18-Comparison of Stocking Policies for Common Inventory Models used at The Boeing Company.

As show below (Caplice, 2011, p. 3), inventory planning is conducted in cycles. A strategic inventory optimization model balances investment with performance by minimizing the cost of initial spares subject to a fill rate constraint. A tactical model is run on a day-to-day basis as stock levels require rebalancing, either because reorder point has been reached and the stocking policy is being reviewed due to the nature of the part,
or because the supply chain data – the price, lead time, demand, or other parameters have changed and the stocking policy must be revisited. Operational activities are carried out on an order-by-order basis during supply chain execution.

Figure 19-The relationship between Strategic, Tactical, and Operational Inventory Planning

The goal of this analysis is demonstrate that simulation analysis can be applied to the part-at-a-time tactical evaluation of stocking policies, in concert with the strategic optimization goals of a global inventory optimization model. By keeping the fill rate (specifically, the Expected Backorder (EBO) target) constant, changes to the demand, price, lead time, and other parameters may be made at the part-at-a-time tactical level, in keeping with the overall stocking strategy of the strategic inventory optimization model.
8.1.1 Target Curve

The Stocking Policy Simulator was exercised for 1,000 iterations using random demand estimated through Stochastic Dynamic Forecasting. The target curve for the four stocking policies is shown below.

The higher the fill rate the better. As the Target Curve for fill rate shows, in the figure below, the CNATRA heuristic stochastically dominates the SPO Strategy stocking policy, which in turn dominates VMetric-XL, which dominates the Wilson EOQ equation. Note that these Target Curves were run by simulating Part Number 5911804-1; results for other parts would vary significantly. In particular, the CNATRA heuristic allocates inventory by lead time and demand, so the resulting fill rate will vary on a part-by-part basis.

![Cumulative Distribution Function (CDF)](image)

Figure 20-The Target Curve, or Cumulative Distribution Function (CDF), for Fill Rate for Plan A (SPO Strategy, in blue), Plan B (VMetric-XL, in red), Plan C (Wilson EOQ, in mauve), and Plan D (the CNATRA heuristic, in orange).

The SPO Strategy analytic model reports that the stocking policy for this part should achieve an 88% fill rate, and indeed the simulator indicates that this policy should achieve 92%. The 10% Value at Risk (VAR) shows that one out of every ten years, fill rate for this part could be as low as 74%. Because fill rate caps out at 100%, more
illuminating than the 10% Value at Gain (VAG) is to refer to the CDF above, where there is about a 50% chance that fill rate will exceed 95%.

The Wilson Economic Order Quantity (EOQ) equation assumes constant demand, so that replenishment stock arrives the day that inventory drops to zero. With variable demand, there will be a 50% chance of running short before replenishment stock arrives. Therefore, as the table below shows, it is not surprising that the Wilson EOQ has a mean fill rate of 84%.

The VMetric-XL stocking policy was estimated based upon the Expected Backorder (EBO) target resulting from the SPO Strategy stocking policy. Because both VMetric-XL and the Wilson EOQ have the same reorder point, we know that VMetric-XL is not assigning any safety stock. A review of the equation shows that this is because the backorder target is resulting in a low calculation for safety stock factor. The Target Curve for VMetric-XL was expected to be similar to that of SPO Strategy; the fact that the SPO Strategy Target Curve is stochastically dominant indicates that the there is a problem with the way the EBO target has been implemented which should be revisited! In addition, the Target Curve can actually be used to validate the corrections.

The CNATRA heuristic, for this part, results in a 10% VAR of only 87% fill rate. This is either a superior stocking strategy, or one with excess inventory that could stand to be leaned out. This question will be revisited in the analysis of Multiple Criteria.
## 8.1.2 Multiple Criteria

The lower the Net Present Value (NPV) for Total Relevant Costs, the better. As the Target Curve for fill rate shows, in the figure below, the Target Curves for the Wilson EOQ and VMetric-XL stocking strategies stochastically dominate the SPO Strategy stocking policy, which in turn dominates the stocking policy of the CNATRA heuristic. As noted, these Target Curves were run by simulating Part Number 5911804-1; results for other parts would vary significantly.

If the goal is to achieve at least an 88% fill rate for this part, then clearly the Wilson EOQ and VMetric-XL stocking strategies achieve their lower NPVs by running short of parts, as they are achieving mean fill rates of 84% and 87% respectively. Since the Wilson EOQ and VMetric-XL stocking strategies have the same ROP, with the VMetric-XL policy having a large ROQ, it is not surprising that they have similar curves. As noted previously, the Target Curve for VMetric-XL suggests that the current implementation of

---

<table>
<thead>
<tr>
<th>Fill Rate(A) SPO Strategy</th>
<th>Fill Rate(B) VMetric-XL</th>
<th>Fill Rate(C) WILSON EOQ</th>
<th>Fill Rate(D) CNATRA</th>
<th>Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% Value at Risk (P10)</td>
<td></td>
<td></td>
<td></td>
<td>10% chance NPV low as this amount</td>
</tr>
<tr>
<td>74%</td>
<td>69%</td>
<td>63%</td>
<td>87%</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td></td>
<td>The expected value, w/50% probability</td>
</tr>
<tr>
<td>92%</td>
<td>87%</td>
<td>84%</td>
<td>96%</td>
<td></td>
</tr>
<tr>
<td>10% Value at Gain (P90)</td>
<td></td>
<td></td>
<td></td>
<td>10% chance NPV exceeds this amount</td>
</tr>
<tr>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

Table 7-10% Value at Risk and Gain (VARG) for the SPO Strategy, VMetric-XL, Wilson EOQ, and CNATRA stocking policies for Fill Rate.
backorder target, as a way to equate the SPO Strategy and VMetric-XL stocking policies, is suspect!

Two stocking policies achieve the desired 88% fill rate. The SPO Strategy stocking policy has a mean NPV of $5,977 as compared with CNATRA at $6,696. The industry rule of thumb is that inventory optimization lowers the initial cost of spares by 25% compared to not optimization, as indicated here. Of course, a fair comparison would require evaluation of all parts in an entire support program; here, only one part is being compared.

Figure 21-The Target Curve, or Cumulative Distribution Function (CDF), for Fill Rate for Plan A (SPO Strategy, in purple), Plan B (VMetric-XL, in orange), Plan C (Wilson EOQ, in blue), and Plan D (the CNATRA heuristic, in red).

Implications for Contracting: The 10% Value at Risk and Gain (VARG) table indicates that with variable demand, the NVP of the Total Relevant Costs for the SPO Strategy stocking policy can be expected to range from as little as $4,990 to as much as $7,009. What this indicates is that one should not estimate annual costs for a support program on a part-by-part basis; rather the aggregate costs should be estimated, establishing a value such as the 80% or 90% VAG for a firm fixed price (FFP) contract, or establishing a value such as the 60% or 70% VAG as the base for a cost plus incentive fee (CPIF)
contract. Further, the best stocking policy most consider multiple criteria, leading to the decision rule that the stocking policy with the lowest NPV, which achieves the desired fill rate, should be selected.

<table>
<thead>
<tr>
<th></th>
<th>NPV(A) SPO Strategy</th>
<th>NPV(B) VMetric-XL</th>
<th>NPV(C) WILSON EOQ</th>
<th>NPV(D) CNATRA</th>
<th>Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% Value at Risk (P10)</td>
<td>$4,990</td>
<td>$4,431</td>
<td>$4,484</td>
<td>$5,714</td>
<td>10% chance NPV low as this amount</td>
</tr>
<tr>
<td>Mean</td>
<td>$5,977</td>
<td>$5,461</td>
<td>$5,444</td>
<td>$6,696</td>
<td>The expected value, w/50% probability</td>
</tr>
<tr>
<td>10% Value at Gain (P90)</td>
<td>$7,009</td>
<td>$6,531</td>
<td>$6,455</td>
<td>$7,543</td>
<td>10% chance NPV exceeds this amount</td>
</tr>
</tbody>
</table>

Table 8-10% Value at Risk and Gain (VARG) for the SPO Strategy, VMetric-XL, Wilson EOQ, and CNATRA stocking policies for Net Present Value (NPV).

8.2 Acquisition Policy (Evaluation continuous vs. periodic review policies)

As mentioned previously, acquisition policy is modeled by assuming that stocking policy was set using a continuous review policy model, but that annual funding cycles result in a de facto periodic review policy. For this model, Plan A represents a one (1) month review period (the flexible case) and Plan B represents a twelve (12) month review period (the fixed case). Otherwise, the stocking policy was identical. This case highlights what can happen when inventory policy and fiscal policy are not aligned.

8.2.1 Target Curve

Plan A (Continuous Review, in blue) stochastically dominates Plan B (Periodic Review, in red), where the higher fill rate is better. Plan A has a mean fill rate of 91.9%,
compared to 80.3% for Plan B, over 1,000 simulations. Note that these curves are non-linear, which we know because they do not follow a standard normal S-curve, and because of the kinks or corners in the curves.

Figure 22-The Target Curve, or Cumulative Distribution Function (CDF), shows that Plan A (Continuous Review performed Monthly) stochastically dominates Plan B (Periodic Review Performed Annually) for fill rate, where higher is better.

The 10% Value at Risk (VAR) is determined by the lower 10% VAR arrow at a Cumulative Distribution Function (CDF) value of 0.10. For this arrow, we see that Plan A is at a fill rate of approximately 59%, whereas Plan B is at approximately 74%. Therefore, Plan B is more attractive at the CDF value of 0.10 (the 10th percentile). At the 10% Value at Gain (VAG), represented by the upper arrow at a CDF value of 90%, both plans cap out at 100% fill rate.
The conclusion is that stocking policy and acquisition policy go hand in hand. When a company selects a continuous review stocking policy, and writes a flexible contract that allows purchasing month to month as stock levels reach reorder point, the conditions to achieve the optimized fill rate goals are in places. When a company instead signs up for a rigid annual contract that fixes the initial buy required to “plus up” to the optimal stock levels, as well as fixes future purchases based on average demand for spares parts, a periodic resupply contract has been signed. In this case, the stocking policy must be changed from continuous review (with monthly buys to stock level) to periodic review (with annual buys to stock level), requiring that the twelve (12) month review period be added to the procurement lead time. This will significantly increase the required initial spares, or initial capital expenditure (CAPEX), recommended by the inventory optimization model.

### 8.2.2 Multiple Criteria

Plan B (Periodic Review, in red), where the lower Net Present Value (NPV) of Total Relevant Costs is better, stochastically dominates Plan A (Continuous Review, in blue). Plan B has a mean NPV of $5,244, compared to $6,010 for Plan A, over 1,000
simulations. However, Plan B also has a mean fill rate of 80.3%, compared to 92.2% for Plan A. The Fill Rate and NPV criteria appear to be in conflict, or are they?

Figure 23-The Target Curve, or Cumulative Distribution Function (CDF), showing the 10% Value at Risk (VAG) and 10% Value at Gain (VAG) for Plan A (Continuous Review, in red) and Plan B (Periodic Review, in red)

The 10% VAR and 10% VAG table for the NPV of Total Relevant Cost tells an interesting story. Ostensibly, the lower the Total Relevant Cost, or NPV of Order Cost + Holding Cost, the better. However, that assumes that both plans achieve the desired fill rate goals. What the CDF for NPV, and the table below, indicate is that Plan B (Periodic Review) is running short on inventory, because there is insufficient safety stock to support a twelve (12) month review period!
### Table 10 - The Value at Risk and Gain for the Continuous Review/Flexible vs. Periodic Review/Fixed Scenarios

<table>
<thead>
<tr>
<th></th>
<th>Plan A (Continuous Review/Flexible)</th>
<th>Plan B (Periodic Review/Fixed)</th>
<th>Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% Value at Risk (P10)</td>
<td>$5,011</td>
<td>$4,110</td>
<td>There is a 10% chance NPV will be as low as this amount</td>
</tr>
<tr>
<td>Mean</td>
<td>$6,010</td>
<td>$5,244</td>
<td>The expected value, with a 50% probability</td>
</tr>
<tr>
<td>10% Value at Gain (P90)</td>
<td>$7,010</td>
<td>$6,238</td>
<td>There is a 10% chance NPV will be as high as this amount</td>
</tr>
</tbody>
</table>

The conclusion is that the Fill Rate and NPV criteria must be considered together. An appropriate decision rule is to select the stocking policy with the lowest NPV which achieves our desired Fill Rate goal. In the case of acquisition policy, the stocking policy and acquisition policy must also be consistent.

### 8.3 Jensen’s inequality

Jensen’s Inequality states that the average of all the possible outcomes associated with uncertain parameters generally does not equal the value obtained from using the average value of the parameters. Essentially, this says that for systems with a non-linear response (which comprises most engineering systems), the value of the expected input is not equal to the expected value of probability-weighted input scenarios.

Whether the Total Relevant Cost function for a stocking policy model is truly linear will be evaluated. The formula $E[f(x)] \neq f[E(x)]$ holds true if $f(x)$ is convex function. The usage (annual demand * unit price) of spare parts is a linear function of the operating hours. Since there are no lost backorders in this scenario, all demand is eventually filled, so usage would be a linear function. The Total Cost is should be a convex function,
since holding costs are capped under high demand scenarios when inventory runs short. Whether the fill rate function is sensitive enough to test for Jensen's inequality will also be evaluated.

Two scenarios were evaluated for Part Number 5911804-1, CAGE 99167, Nomenclature BOOT, AIRCRAFT, MATER was modeled. The Contractor and Government Entity (CAGE) Code identifies the part manufacturer.

a. Constant Demand - Demand for this part averages 6.4 units per month. Since parts are ordered in units of each, a recurring pattern of six or seven units monthly was created which averaged to 6.4 units annually.

Figure 24-Constant demand results in stable inventory levels, as depicted by the light green line of inventory position.
b. Variable Demand – Using Stochastic Dynamic Forecasting, and starting with 6.4 units per month, random demand was simulated and then rounded to the nearest integer.

![Figure 25-Variable demand results in unstable inventory levels, as depicted by the light green line of inventory position](image)

Figure 25-Variable demand results in unstable inventory levels, as depicted by the light green line of inventory position

c. Fill Rate test of Jensen’s Inequality - The Cumulative Distribution Function (CDF) for fill rate, based upon 1,000 simulations of variable demand, shows that for the constant demand scenario in blue (A), we always achieve 100% fill rate. For the variable demand scenario in red (B), we have a 50% chance of reaching 92.7% fill rate, and indeed the calculated fill rate for this part was 88%. However, when this fill rate is not achieved, it dips as low as 40%! Since fill rate caps out at 100%, the
red curve does not form a standard S-curve, demonstrating (along with the bend at 95% fill rate) that fill rate is non-linear.

Figure 26-The Target Curve, or Cumulative Distribution Function (CDF), shows that fill rate with variable demand is non-linear, as show by the corner in the red graph, as fill rate caps at 100%. The expected fill rate for steady demand, of course, never varies, as shown by the vertical dashed blue line.

d. NPV test of Jensen’s Inequality – Net Present Value (NPV) follows a traditional S-curve when variability of demand is simulated. The mean NPV with constant demand in blue (A) is $5,442, as compared to $5,975 with variable demand in red (B). Since NPV of the Total Relevant Costs only considers holding cost and order cost, a lower NPV is better. The difference in costs due to placing additional orders, and additional holding time, with the variable scenario. The assumption that demand is constant is clearly false, based upon the significant variability of the original data. Jensen’s Inequality holds, because the value of the expected input is not equal to the expected value of probability-weighted input scenarios.
Figure 27-CDF for Net Present Value (NPV) demonstrates Jensen’s Inequality: the mean NPV with constant demand, in blue, is less than the mean NPV with variable demand.

One of the fallacies of assuming constant demand is that fill rate never varies. With variable demand, there is a 50% chance that fill rate will be less than 92.7%, and as the Value at Risk chart shows, a 10% chance that fill rate will be less than 77%.

<table>
<thead>
<tr>
<th></th>
<th>Plan A (Constant Demand)</th>
<th>Plan B (Variable Demand)</th>
<th>Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% Value at Risk</td>
<td>100%</td>
<td>77%</td>
<td>There is a 10% chance that fill rate will be as low as this amount</td>
</tr>
<tr>
<td>Mean</td>
<td>100.0%</td>
<td>92.7%</td>
<td>The expected value, with a 50% probability</td>
</tr>
<tr>
<td>10% Value at Gain</td>
<td>100%</td>
<td>100%</td>
<td>The VAG caps out at 100% fill rate</td>
</tr>
</tbody>
</table>

Table 11-The Value at Risk and Gain for the Fixed versus Variable Demand Scenarios
The lesson learned, from considering Jensen’s Inequality, is that analysis based upon average demand rates will be inaccurate.

9.0 Discussion of Results

Evaluating stocking policy requires consideration multiple criteria, namely fill rate and Net Present Value (NPV). The best stocking policy achieves the desired fill rate at lowest Total Relevant Cost (TRC), where TRC encompasses the NPV of order cost and holding cost. The Boeing Company has a low tolerance for risk: if a contract specifies a 90% fill rate, that fill rate should be achieved. From a contractually standpoint, the company is also obligated to manage inventory in a manner that can reasonably be expected to achieve these results.

9.1 The Preferred Design

**Acquisition Policy:** The preferred stocking policy should be in concert with the acquisition policy. Therefore, given an annual Government funding cycle, The Boeing Company should stock to a twelve (12) month periodic review policy. Since this requires a larger capital expenditure (CAPEX) for initial spares, due to the added twelve (12) months of pipeline inventory, the company instead should develop a financial business case for changing acquisition policy to (a) fund the “plus up” to achieve optimal stock levels, and (b) allow a funding vehicle for flexible monthly expenditures.

**Long Term Contracting:** As demonstrated by Jensen’s Inequality, the average of all the possible outcomes associated with uncertain parameters generally does not equal the value obtained from using the average value of the parameters. The Boeing Company should shift from basing long term contracts on average requirements, to basing requirements on an expected range of values.
9.2 Flexible Stock Level Policies

**Flexible Stocking Policies**: Four flexible stocking policies were reviewed: SPO Strategy, VMetric-XL, Wilson EOQ, and CNATRA. The conclusion is that multiple criteria - Fill Rate and NPV - must be considered together in order to choose the appropriate stocking policy. An appropriate business rule is to select the stocking policy with the lowest NPV which achieves the desired Fill Rate goal.

**Next Steps for Flexible Stocking Policies**: The evaluation of the Target Curve revealed a need to further investigate differences between the SPO Strategy and VMetric-XL inventory optimization models. In particular, the use of the Expected Backorder (EBO) target should be reviewed. For example, the VMetric-XL model may calculate EBO as an annual number, whereas SPO Strategy may calculate EBO as the value occurring within procurement leadtime. If this is the case, then these numbers must be adjusted before they can be compared, and before they can be correctly employed in the stocking policy simulator.

**Sensitivity Analysis**: Addition analysis of other part numbers, not described in this report, shows that the lower the demand and the longer the lead time, the less sensitive fill rate is to adjusting the time between reviewing inventory position. That is, the impact of selecting a continuous vs. periodic review policy increases as the review period exceeds order cycle time (the time between orders). Thus, if the average time between orders is 30 days, and inventory position is checked annually, certain stockout is likely. On the other hand, if the time between orders exceeds one year, acquisition policy may not have an immediate impact.

**Next Steps for Sensitivity Analysis**: A trade study should be conducted to look at the aggregate impact of implementing a continuous review order policy when the actual practice is periodic review. This trade study will be conducted as part of my master’s
thesis, and will be used to inform ongoing contact negotiations between The Boeing Company and the US Navy.

10.0 Discussion of Lessons Learned

Incorporating flexible approaches for leveraging uncertainty and proven simulation templates from ESD.71 Engineering Systems Analysis for Design, my existing collection of part-at-a-time analysis spreadsheets, inventory policy formulae from ESD.260 Logistics Systems, and statistical analysis techniques from ESD.250 Analytical Methods for Supply Chain Management has enabled me to create a semi-seamless application for part-at-a-time tactical asset management. Realizing that this analysis can be conducted in concert with the optimized goal of an inventory optimization model by keeping the backorder goal aligned, it is now possible for asset managers to evaluate alternate stocking policies, or make tactical changes to incorporate updates to price, procurement lead time, and demand.

A flexible approach offers tremendous benefits for supply chain design. Although often applied to large engineering projects, or Real Options, flexible design can be applied to evaluation of inventory stocking policies. The problem with traditional inventory optimization models it that:

- They are seen as complicated black boxes
- They often require such a large infrastructure of IT, strategic planners, and asset managers to operate that it is easy (and has proven costly) lose sight of what is happening within the model
- It is all too easy to meet a fill rate target and ground a fleet. An inventory optimization model buys the lowest cost mix of parts to achieve a goal, which can be achieved by skewing the purchase towards high volume, low dollar piece parts.

The Excel model developed for this project is a fully functional supply chain simulator, which evaluates parts one at a time. This is a fine enough granularity that asset managers can actually grasp the impact of variability of demand, via the Stochastic
Dynamic Forecasting module. Asset managers can evaluate the impact of the stocking policy recommended by the inventory optimization model, via the Line of Balance and Visual Line of Balance worksheets. They can evaluate simulations comparing two stocking policies, based on NPV of Total Relevant Costs and Fill Rate, and review the results of a Separate-Variances t-test for samples with unequal population variances.

The prototype stocking policy simulation is remarkably full featured:

- Uses the classic inventory (s,S) order point, order-up-to-level model to calculate expected fill rate based upon supply chain data and a given reorder point and reorder quantity. This provides a check against and inventory optimization model, as well as a check against the simulated results.
- Models parts arriving procurement lead time away from order date, showing the impact of an inventory shortfall on the required time to recover to a healthy inventory position
- Models current inventory position: on hand, due-in, and backordered inventory
- Models a list of up to 60 due-in orders, by due-in date
- Allows flexibility to simulate multiple parts, by creating a worksheet named for each new part and simply referring to the part number to switch parts
- Uses Stochastic Dynamic Forecasting to visually depict variability of demand over time
- Uses a Visual Line of Balance worksheet to graphically depict inventory policy, showing the classic saw toothed Economic Order Quantity (EOQ) curve for constant demand, and a more chaotic curve when variability is incorporated.
- Automates comparison of two scenarios through hypothesis testing
- Automates the analysis, demonstrating that by preloading supply chain data and historical demand data, creation of a family of tactical analysis simulators would be eminently practical

Unexplored is the promise of applying Real Options to create flexible supplier contracts in a methodology known as Range Planning and Performance. Once stocking policies have been determined, the next frontier for lowering supply chain costs is to decrease
downside risk and increase upside gain by partnering with key suppliers to guarantee buys within a predetermined range, offering stable production to suppliers, flexible purchasing to the contractor, and lowered holding cost on finished goods by reducing supplier lead times. This process is fully described in APPENDIX B – Range Planning and Performance.

Perhaps most importantly, the collection of techniques will enable me to bring new insights to The Boeing Company on flexible warehousing approaches to sustaining new aircraft being sold in the southeast Asian market, conveying the supply chain risk of stocking policies on the F/A-18E/F program, and making the business case for continued investment in new people, tools, and processes for turning supply chain uncertainty into a competitive advantage.
11.0 APPENDIX A – Biography for Randolph L. Bradley

BIOGRAPHY FOR RANDOLPH L. BRADLEY

As a Technical Fellow and Certified Professional Logistician (CPL) within Boeing’s Integrated Defense System’s Supply Chain Management organization, Mr. Bradley oversees the strategic design and execution of optimal supply chain programs. A logistics expert with two decades in the field, he has maximized equipment availability and reduced the risks and costs of maintaining equipment in performance-based programs for the services and foreign customers.

Mr. Bradley developed an innovative patent-pending business model to optimize supply chain processes. This model focused on advanced data cleaning techniques to improve forecasting accuracy while minimizing inventories, cost and risk. For these achievements, he received Boeing’s Special Invention Award, an honor reserved for only the very top innovators at the Company.

Mr. Bradley is also credited with developing the Boeing Lifecycle Integrated Support Solutions (BLISS) project, which introduced inventive material management methods. His BLISS process manages spares parts and repair services for heavy industries with equipment having a long life, using proprietary processes and commercial off-the-shelf (COTS) tools. This proven approach has achieved dramatic results by lowering customers’ inventory investments by 25 percent and day-to-day asset management costs up to 15 percent while maximizing the availability of their heavy equipment.
Range Planning and Performance

The current analysis paves the way for a future Real Options approach to procurement contracts for aviation spare parts, while originated based on discussions with Prof. Blake Johnson of Stanford University in 2009-2011. The current project set the stage by (a) demonstrating the impact of uncertainty in demand upon stocking policy, (b) creating a financial baseline against which Range Planning and Performance can be compared, and (c) delivering a Stochastic Dynamic Forecasting module which can be incorporated to generate random estimates of future demand.

What is the system? What does it include, and what does it exclude?

Given a Boeing program which holds inventory, either Boeing or customer owned, and given an optimal inventory plan from an inventory optimization model, is this as good as it gets?

Recognizing that the US military, foreign services, and Boeing’s competitors use the same inventory optimization models, if optimal is as good as it gets, where is Boeing’s competitive supply chain advantage? Flexible supplier agreements known as Range Performance Management contracts, pioneered by Stanford University professor Blake Johnson, will be evaluated to create win-win flexible contracts with Boeing’s supplier partners. The aim is to show that flexible supplier contracts can turn supply chain uncertainty into a Boeing competitive advantage at lower cost than the company’s customers could achieve on their own.

The goal of Range Planning and Performance, which is based on economic theory known as Real Options, is to create pull based parts availability. Suppliers commit to deliver parts to Boeing within a defined range of demand. Boeing sets the ranges based on a stochastic analysis of historical part demand, knowing the desired service levels set by the strategic inventory optimization model. The benefit lies in substituting committed supply availability at pull based lead time for Finished Goods Inventory (FGI), lowering the request investment in inventories of spare parts.
The goal is to create a financial business case for innovative Range Planning and Performance supplier contracts to manage and/or reduce procurement lead time, and as a result optimal inventory, given uncertainty in demand and lead time. A successful business case would lead to (a) development of an Excel based tool for generating flexible supplier contracts, known as Range Planning and Performance, based on a contract template and supply chain data available from an inventory optimization model, and (b) a pilot to establish Range Planning and Performance contracts for a targeted number of sourcing relationships.

**The Principal Design Levers or Variables**

Range plans utilize all supply chain "levers" to manage uncertainty, including production, material sourcing, and capacity, in addition to inventory.

- **Today:** Pull-in and push-out the best guess plan, based on a strategic inventory optimization, subject to run-rate constraints and liabilities.
- **Range plan:** Flex plan up and down within an operating range that has been proactively established
The Benefits to Boeing

- Obtain "run level service level" (service level where demand is variable and trending) since the supplier is intelligently managing inventory.
- With Vendor Managed Inventory (VMI), can put inventory at the supplier to eliminate Boeing held inventory. Exchange Finished Goods Inventory (FGI) for high quality planning information provided to supplier. Gets Boeing out of the business of holding inventory except for a small amount of inventory held for internal planning purposes.
- Lower inventory buffer based on reduced lead time and guaranteed supply flexibility.
- Reduces inventory and increases service level.
- Increase service levels on parts with annual demand of 24 or greater.
- Obtain known parts availability at short lead times committed to by suppliers.
- Size the upside based on what’s needed to meet the service level.
- Can always change ranges lead time out, since supplier can vary production capacity over lead time.

The financial benefits to Boeing will be quantified using a five year Net Present Value (NPV) analysis, comparing part price and inventory holding cost between the baseline business as usual scenario, and the new Range Planning and Performance Scenario. Shown below is an example of a NPV analysis as an illustration.
The Benefits to Suppliers

- Easy for supplier to implement: plan to the maximum delivery level in the Material Requirements Planning (MRP) system. The MRP system ensures that enough materials are ordered within lead time to guarantee production capacity for the maximum buy.
- Termination liability is easy to calculate: can determine exactly how much material must be on order, at each step in the lead time, to support the contract. This is important for Performance Based Logistics (PBL) contracts which are subject to re-compete.
- Higher quality planning information.
- Boeing provides the right incentives and risk sharing, increasing business value over traditional contracts.

Measures of Performance

- (a) Net Present Value (NPV) of Total Costs, (b) NPV of End of Year Inventory, (c) Inventory Turns and Days Inventory, (d) Inventory Quality (absolute value of the distance of where I am vs. where I want to be)
- (a) Cycle Service Level, and (b) Fill Rate
- Realized lead time (for example, the supplier stated lead time is 85 days, but varies between 60 and 180 days, versus committed supply lead time under RPM)
- These KPIs are measured at the part level
- An Monte Carlo simulation model will be developed in Excel to analyze the effect of the design variables on the benefits or performance of the system

What are the main contextual factors that will affect the value of its performance?
Forecasts are volatile:

- **Supplier Risk**
  - What level to plan to?
  - Capacity, materials, production…
  - Incentives and risk sharing for upside availability?

- **Buyer Risk**
  - Supply constraints + lead time to resolve?
  - Liability?

Demand is variable:

- **Supplier Risk**
  - How much FGI? Work In Progress (WIP)?
  - Incentives to hold it? (unforecasted demand)

- **Buyer Risk**
  - Supply availability and lead time?
The next spiral of development on the tactical decision support toolkit should incorporate the following list of enhancements:

a. Verify that no due-in parts are recorded for memory variable Data_Due_In_Assets, if a table of due-in assets is also used
b. Create a flag to commence simulation on either system date, or a fixed date
c. Create a chart of fill rate, by month, over 20 scenarios, similar to the Stochastic Dynamic Forecasting
d. Incorporate (R,s,S) Periodic-Review, Reorder Order Point, Order-Up-to-Level policy. (a) Add EOQ formula. (b) Incorporate periodic review period in spreadsheet (26NOV11-SAT).
e. As a validation, compare the Stochastic Dynamic Forecast to an existing Poisson demand forecast, using an empirical order quantity distribution, using a two-sample test with equal variance (pooled-variance t-test for differences in means)
f. Implement Zero Inflated Poisson (ZIP) regression (Ref: email to Prof. Stefan Scholtes 29NOV11-TUE)
g. Incorporate a stocking policy formula for Poisson demand
h. Incorporate stocking policy logic for reparable parts
  i. Add a level and trend (Holt’s method) to the Stochastic Dynamic Forecast
  j. Add a triangular distribution to the Stochastic Dynamic Forecast, to account for long term uncertainty in operating hours, which can vary significantly (and independently) of the demand forecast itself
k. Incorporate average days delay as a measure of merit
l. Add Stock Out and Lot Size Calculations to the stocking policy formulae
m. Run a 10 year versus a 5 year forecast, to smooth out early uncertainty due to long procurement lead times
n. Add inventory turns as a measure of merit
o. Add a multi-way table to speed calculations
p. Adjust table size, or dynamically adjust table size using Visual Basic, from 2,000 to 1-n rows to speed calculations/run time (26NOV11-SAT)
q. Estimate orders per month based on a regression of total demands per month on x-axis versus number of orders on y-axis. Calculate orders filled assuming an average order quantity, and knowing how many demands were filled from shelf stock. Note: may not be necessary when aggregating demand into monthly buckets

Additional metrics for evaluating stocking policies should be incorporated in subsequent development spirals:

a. **Net Present Value (NPV) of Average Total Cost** – The NPV, or net present value, is the discounted value of future cash flows, at an appropriate discount rate. Without considering stockout cost, the lowest cost option will always be to stock nothing, because with no inventory there is no holding cost! The total cost equation, extended to incorporate stockout cost, is:
   \[ TC = Dv + A\left(\frac{D}{Q}\right) + vr\left(\frac{Q}{2} + k\sigma_L\right) + C_{\text{Stock Out Type}}P(\text{Stock out type}) \]
ii. Q = order quantity (units)
iii. A = fixed ordering cost ($)
iv. v = unit cost ($ / unit)
v. r = carrying cost ($ / $ / unit time)
vi. D = average demand (units / unit time)
vii. L = order lead time
viii. k = safety stock factor
ix. C_{SO} = Cost of a stock out
x. P_{SO} = Probability of a stock out

b. **NPV of Calculated Total Cost** – The average inventory is the difference between the starting and ending inventory over a year, and is the potential value of the investment at risk of not being sold at the termination of a support contract. The actual Total Cost for each simulation will be calculated.

c. **Inventory Turns** – The number of times inventory is sold over a year. Inventory Turns = Cost of Goods Sold (Usage)/Average Inventory.

d. **Days Inventory** – The average number of days inventory is held before being sold. Days Inventory = Average Inventory/[Cost of Goods Sold (Usage)/365 Days].

e. **Cycle Service Level** (Probability of No Stockout per Replenishment Cycle) – “The fraction of cycles in which a stockout does not occur. A stockout is defined as an occasion when the on-hand inventory drops to the zero level.” (Silver, Pyke, & Peterson, 1998, p. 245)
14.0 APPENDIX D - Correspondence with Prof. Stefan Scholtes

From: Randolph Lewis Bradley [mailto:art2part@MIT.EDU]
Sent: 27 November 2011 20:04
To: s.scholtes@jbs.cam.ac.uk
Cc: Rhonda LeNai Jordan; Richard de Neufville

Prof. Scholtes,

Your new book “Flexibility in Engineering Design” brings to life the real world value of considering flexibility at the inception of major engineering projects. I am implementing stochastic dynamic forecasting, to drive a supply chain simulation for evaluating stocking policies for spare parts held for maintenance, as part of my final project for Prof. Richard de Neufville’s class on Engineering Systems Analysis for Design this fall at MIT. As a Technical Fellow at The Boeing Company, I have access to a plethora of historical data, which leads me to a question on how best to implement stochastic dynamic forecasting using data for service parts with low and intermittent demand patterns.

How to Perform a Log-Transformation with Zero Demand?

My historical data for aircraft maintenance spare parts contains a number of periods with zero demand. While Prof. de Neufville suggested selecting a different period, say three months, estimating requirements for monthly periods is ideal since the inventory position for these parts is reviewed monthly. Further, most data for service parts is sparse, so even aggregating demand into quarterly time buckets does not guarantee that there will never be periods with zero demand. The obvious problem is that when creating a multiplicative model by performing a log-transformation of the demand data to correct for heteroscedasticity, the natural log of zero (0) is undefined. I tried substituting a “Small Number” instead of zero, but found that the smaller the number, the wilder the peaks in my regression model. Can you offer any suggestions on solving this dilemma?

One naïve thought was that if I substitute 0.1 instead of zero when performing a log-transformation, and cap each stochastic demand forecast at the historical mean +/- some number of standard deviations, say five, I avoid the excessive peaks.

I have thoroughly enjoyed your book, and am particularly excited about using stochastic demand forecasting to visually explain variability in demand. Any recommendations on perfecting my use of this technique on demand for service parts would be greatly appreciated.

Cheers,

Randolph Bradley
MIT SCM Class of 2012
art2part@mit.edu
Dear Randolph,

Good to hear about your project. This is very exciting, not least because you have a lot of data. On the notion of zero demand: Log-transforms make only sense when the probability of zero demand is negligible, which is not the case in your example. You need another model if you have zero demands. The correct model for this situation is Poisson Regression (you can look this up in any statistics textbook). You may well have so-called "zero-inflated" data, so will have to use an appropriately adapted Poisson model. The zero-inflation (i.e. more zeros than you would expect from a standard Poisson model) could be due to stock-outs (when sales (which is what you measure) was zero it is possible that there was no demand or that there was demand but no stock).

I copy Yun Shin Lee in, who has recently completed a PhD on dynamic stochastic forecasting and knows much more about this than I.

Thanks a million for finding the errors in the text. I love your spreadsheet. Excellent.

Please keep me informed about the progress of your project.

Best,

Stefan

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+44 (0)1223 339635
15.0 APPENDIX E – Bibliography


Scholtes, S. (2011, 11 29). Personal Email titled "RE: Implementing Stochastic Demand Forecasting". Cambridge, United Kingdom.


