



DMSMS Lifetime Buy Characterization Via Data Mining of Historical Buys

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Lifetime Buys and Bridge Buys

- When an electronic part becomes obsolete...
 - **Lifetime buy** is a mitigation approach that involves the purchase and storage of a part in a sufficient quantity to meet current and (expected) future demands.
 - **Bridge buy** is a buy made to meet current and (expected) future demands *until the next redesign*.
- Lifetime buys and bridge buys play a role in nearly every electronic part obsolescence management portfolio no matter what other reactive or proactive strategies are being followed.
- Determining the appropriate number of parts to purchase at a lifetime buy, is generally easier said than done.

Lifetime Buy Models

How many parts should you buy?

Every organization has developed some institutional knowledge governing lifetime buy *buffer* sizes, e.g.,

- For parts that cost less than x we buy 25% over demand
- For more expensive parts we buy 15% over demand
- Buffer sizes are, however, trumped by minimum buy sizes and what management is willing to signoff on

Models:

- Individual buy quantity models
 - Life cycle cost minimization models
- } The target of these is to determine the buffer size

Stochastic Individual Buy Model

Calculates the quantities of parts necessary to meet a given demand with a specified confidence

- Computes probability distributions of buy quantities for individual part lifetime or bridge buys
- Computes buy sizes that satisfy a specified confidence level
- Computes the probability of being overbought or underbought by a user specified quantity

Inputs

- Length of time you are buying for (in time periods)
- Demand forecast in each time period**
- Length of time needed to design out the part or identify another solution (if necessary)
- Desired confidence level

All quantities can be entered as distributions

**Can be correlated period-to-period

Stochastic Individual Buy Model

(Algorithms)

$$\text{Lifetime buy quantity} = \sum_{i=1}^{\lfloor L \rfloor} Q_i + (L - \lfloor L \rfloor)Q_{\lfloor L \rfloor+1}$$

where

Q_i = marketing recommended buy quantity in time period i (all periods are assumed to have the same length)

L = length of the buy in time periods, i.e., the number of time periods until the part is no longer needed

$\lfloor \cdot \rfloor$ = floor function (round down to the nearest integer).

This model assumes that redesigns (if any) are initiated a sufficient duration prior to L in order to be completed at L .

Stochastic Individual Buy Model

(Stochastic Calculation)

- Both the Q_i and L terms are uncertain (in addition to the length of the redesign).
- Sample values of Q_i and L are generated and used to compute sample lifetime buy quantities.
- Sampling and calculation of lifetime buy quantities is repeated many times to generate a histogram of lifetime buy quantities using a Monte Carlo sampling approach.
- The sampled length of the buy (L_s) is computed using the following relation,

$$L_s = L_{b_s} - (L_r - L_{r_s})$$

- where

L_{b_s} = Sampled forecasted length of buy in time periods

L_r = Length of the redesign (mode) in time periods (planned length of redesign)

L_{r_s} = Sampled length of the redesign in time periods (actual length of redesign).

Note, the length of the time periods cannot be uncertain, but the number of periods can be uncertain

Stochastic Individual Buy Model - Example

Input Data (Demand Forecasts and Forecast Variation):

Time Period	Distribution Type	Mode (None, Triangular, Normal)	Standard Deviation (Normal)	Low (Uniform, Triangular)	High (Uniform, Triangular)	Correlation Coefficient to Previous Period
1	Normal	11000	750			0.5
2	Normal	11000	750			0
3	Uniform			8500	13500	0.9
4	Normal	11000	750			0.9
5	Uniform			8500	13500	0.9
6	Uniform			8500	13500	0.9
7	Uniform			8500	13500	0.9
8	Uniform			8500	13500	0.5
9	Uniform			8500	13500	0.5
10	Uniform			8500	13500	0.5

Input Data (Time Risks):

The length of the buy = 6 time periods

Length of the redesign out (time periods) = 0 to 7.5 (mode = 6) triangular distribution

Input Data (Analysis Control):

Confidence level = 0.9

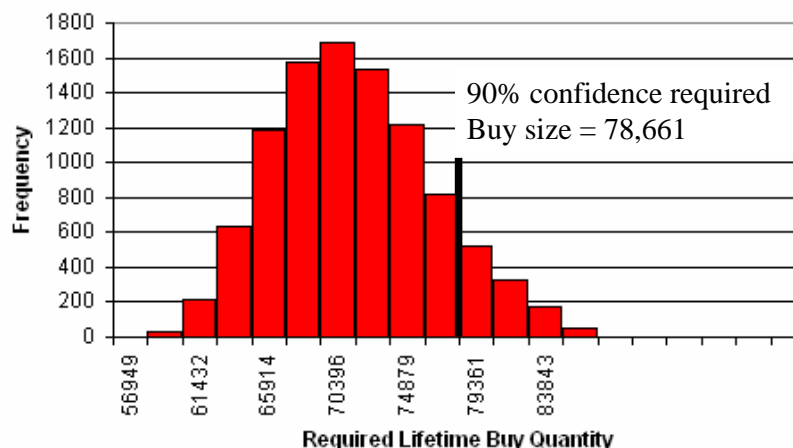
Monte Carlo samples = 10,000

Number of standard deviations to plot = 3

Stochastic Individual Buy Model – Example

Outputs:

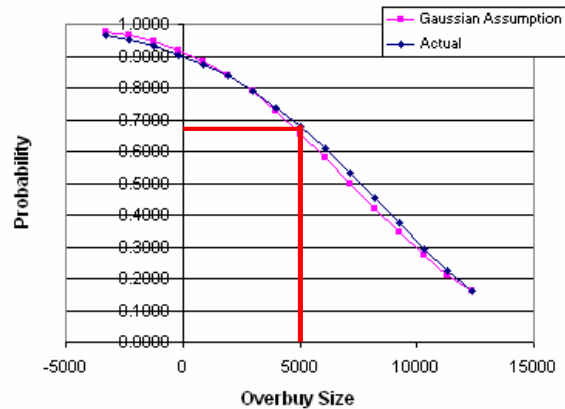
- Buy quantity as a probability distribution
- Buy quantity that satisfies confidence level



Stochastic Individual Buy Model – Example

Outputs (continued):

- Probability of being overbought or underbought by a user specified quantity
- The graph on the right shows that there is a 68% probability that buying 78,661 parts will result in having a surplus of 5000 parts.



Demand Forecasts

This is all dandy, but how do you figure out the demand forecasts?

Depending on the type of system you are managing, you probably have folks who perform demand forecasting, but how accurate have those demand forecasts proven to be in the past?

Motivation for Data Mining

Many organizations maintain a significant history of data associated with the management of electronic parts, e.g., lifetime buy dates and quantities, plus inventory history. If this data could be appropriately mined and interpreted, one could determine:

- Demand forecasting accuracy
- Product termination (date) prediction accuracy
- Design refresh durations (and the accuracy of forecasted durations)
- The frequency and size of over- and under-buys of parts made for bridge and lifetime buys
- Reverse engineering of past decisions to determine implicitly assumed confidence levels
- Frequency of additional last time buys

If these types of quantities could be determined on an organization-specific basis, they would be extremely valuable inputs into the process and optimization of future part management activities.

Supply Chain Data Collected

The following data was collected:

- Part number
 - Date of buy (lifetime or bridge)
 - Projected (expected) completion date
 - Buy completion status (done or not)
 - Product(s) that the buy is for
 - Type of product(s)
 - People involved (originator, materials, finance, etc.)
 - Finance and business organizations, business team
 - Cost per part (at buy)
 - Type of part
 - Quantity forecasted
 - Forecast model used
 - Quantity in stock at buy
 - Quantity purchased (+buffer size)
 - Quantity remaining after completion
 - Quantity known to have been consumed
- 181 complete lifetime and bridge buy records were data mined from a single operation in the supply chain of a major electronic systems OEM

Search for Trends

We looked at the data in many different ways:

- $\frac{\% \text{ Consumed}}{\% \text{ Time Passed}}$

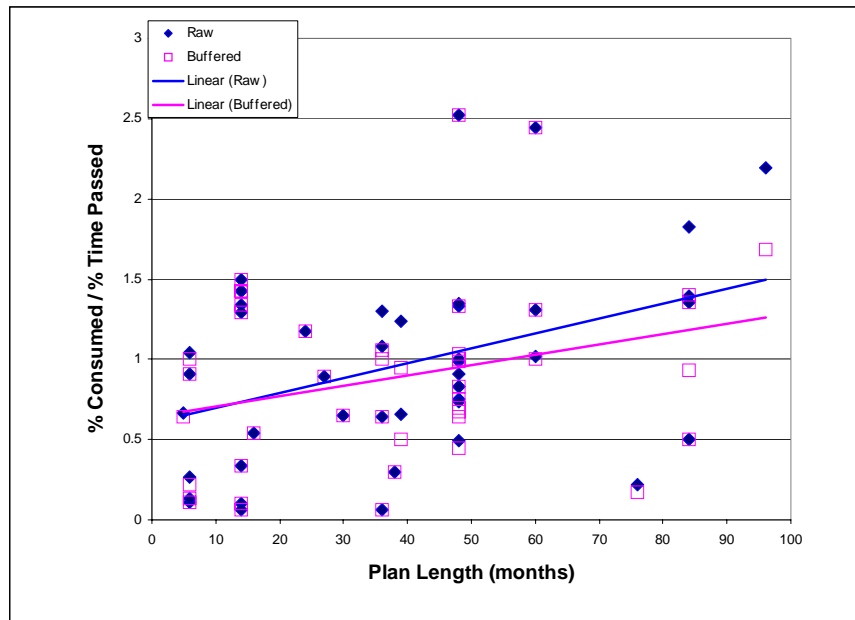
- % Consumed
- Plan Length
- Total Cost
- Total Quantity

Allows complete and incomplete buys to be combined in trends (assuming constant consumption)

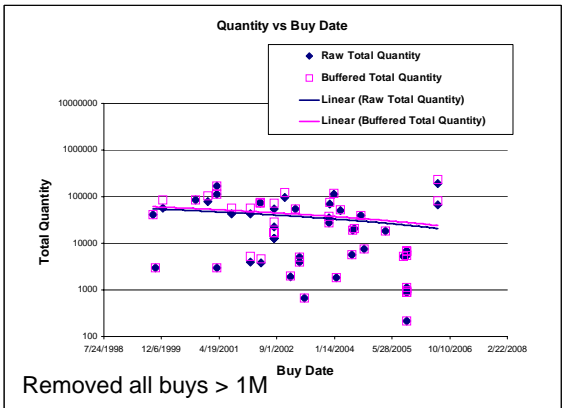
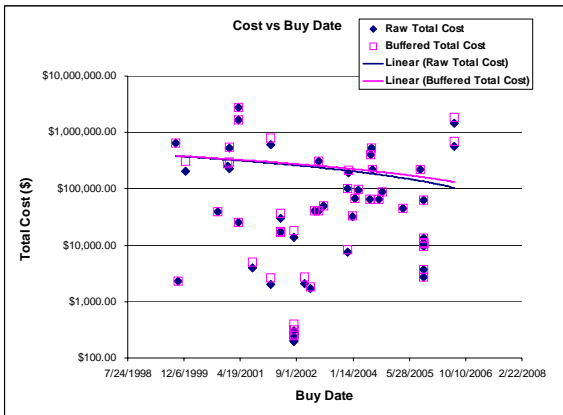
Sorted the data based on:

- Part type
- Product type
- People
- Organizations ...
- Buy Date
- Plan Length
- Part Cost
- Total Buy Cost
- Demand Quantity

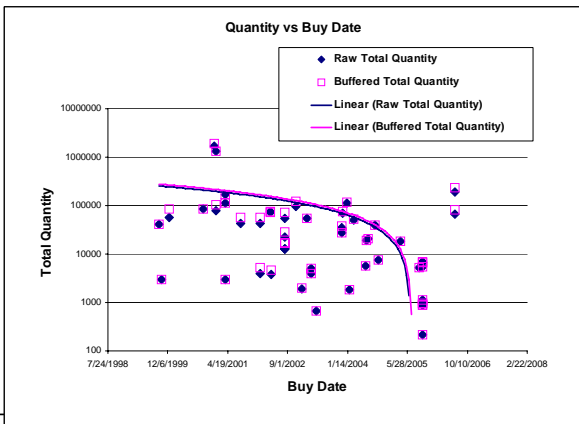
All data points



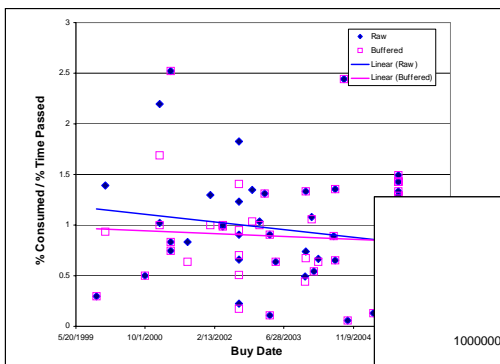
All data points



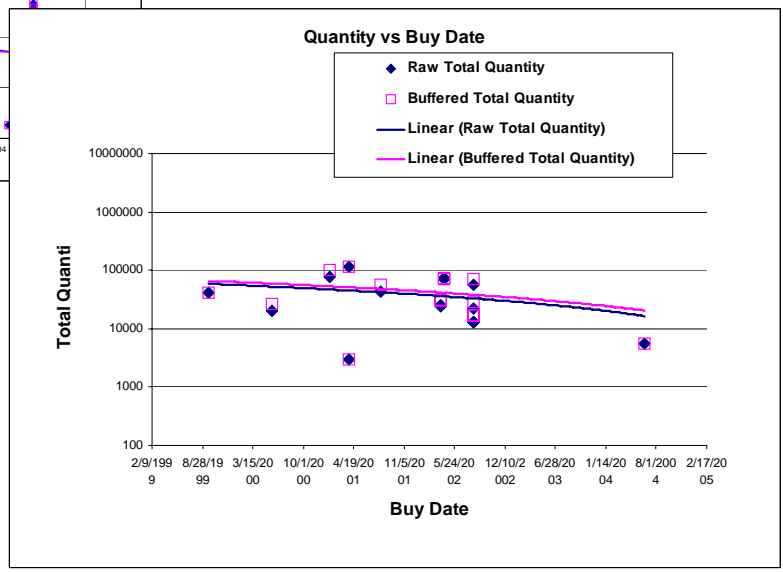
Removed all buys > 1M



All data points



A specific finance organization



Searching for Trends

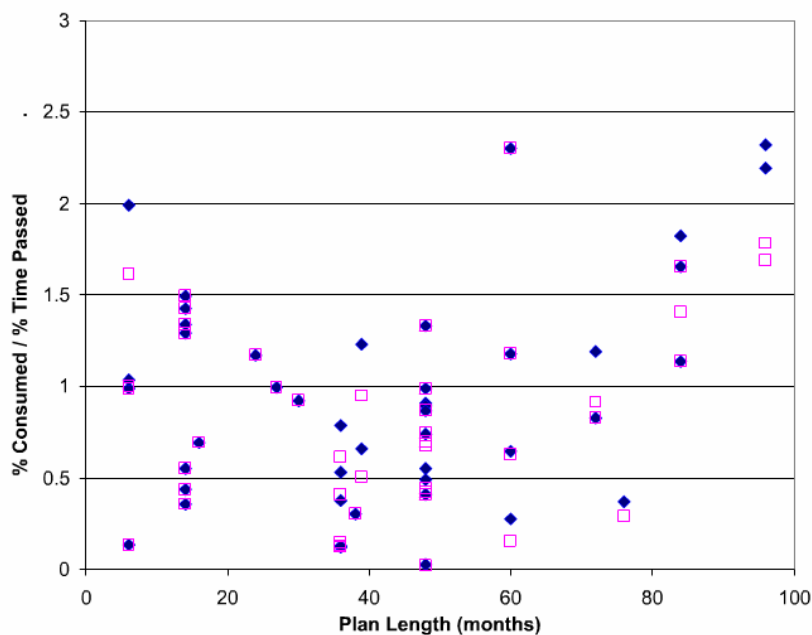
The previous slides show basically a whole lot of nothing! This is not a productive way to look at the data.

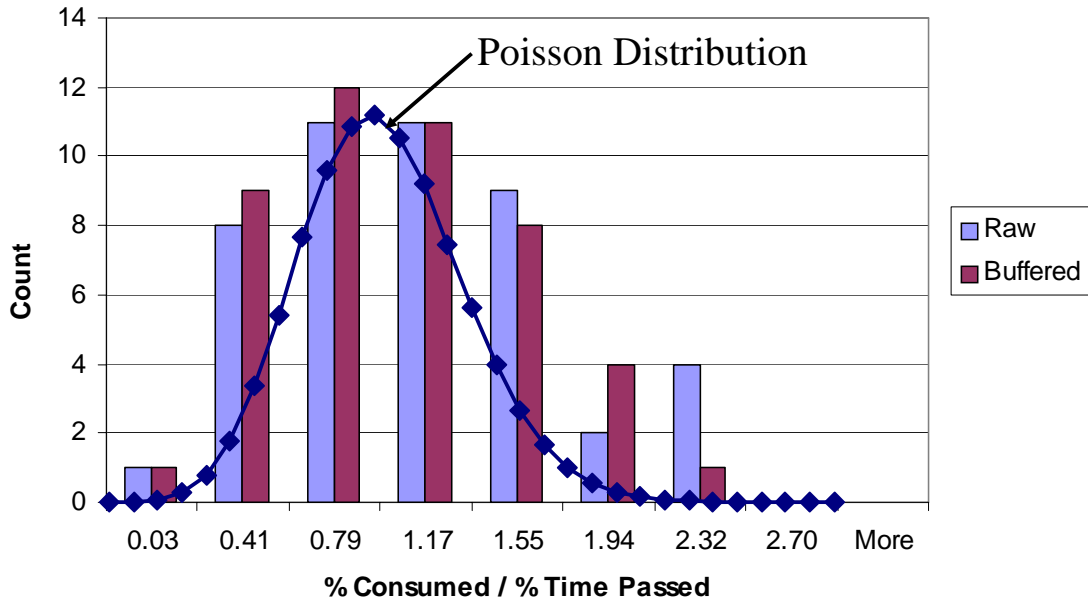
$\frac{\% \text{Consumed}}{\% \text{Time Passed}}$ is the only metric that really allows us to combine the complete and incomplete buy data

Two observations:

- 1) We need to look at a distribution of $\frac{\% \text{Consumed}}{\% \text{Time Passed}}$
- 2) Ideally, this would all be from finished buys (in which case the metric is just %Consumed), but we don't have enough data, so currently active buys are included too and we are making the assumption that their consumption plan is approximately linear when averaged over the whole buy.

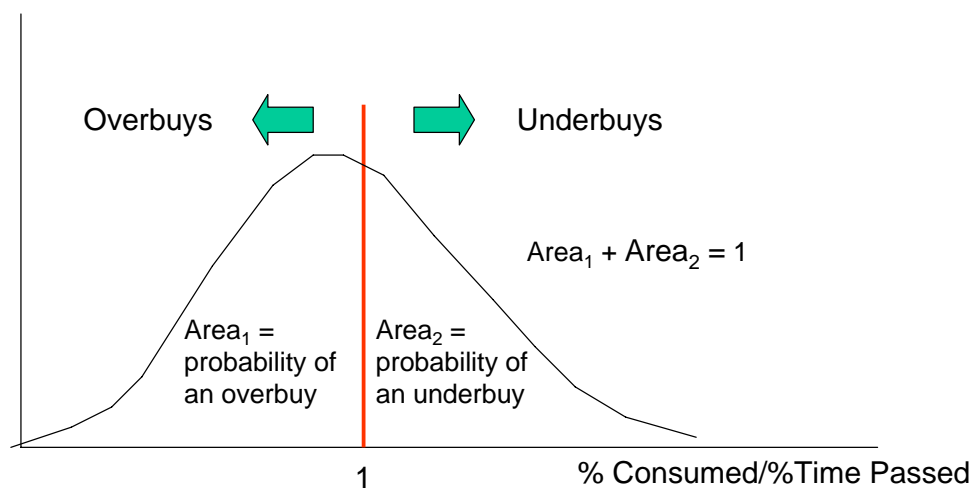
Animation that morphs from this to the diagram on the next slide





Mean = 0.8

What Does This Mean?



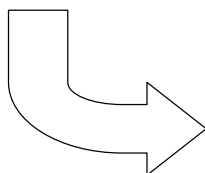
Mean = 0.8 (from slide 19) infers that there has been a tendency to overbuy

How This Result Can Be Used

- 1) Assuming the shape of the distribution on the last slide is the right shape, it can be fit with some functional form (may have to be piecewise – fit separately above and below 1) – this should be done for the “Raw” numbers not the buffered numbers.
- 2) When a demand forecast number is provided, what do we do with it? Construct a version of the distribution found above with the demand forecast at the “1” point. This says that there is an Area_1 probability of the forecast being too large and an Area_2 probability of the forecast being too small – which is the result we mined from the existing data.
- 3) This result defines the demand distribution that goes into the stochastic lifetime buy quantity model.

Where Does the Individual Buy Model Fall Short?

- The individual buy model does not calculate the quantities of parts necessary to minimize life cycle cost (depending on how you are penalized for running short or running long these quantities could be different than what the simple individual buy model gives)
- The individual buy model treats one part at a time – you would really like to analyze all the parts at the same time so that coupling effects between parts are included, e.g., equal run out



Another model called LOTE treats the cost minimization optimization problem:

D. Feng, P. Singh, and P. Sandborn, "Optimizing Lifetime Buys to Minimize Lifecycle Cost," *Proceedings of the 2007 Aging Aircraft Conference*, Palm Springs, CA, April 2007.

<http://www.enme.umd.edu/ESCML/Papers/AgingAircraft07-LTB.pdf>

Summary

- The individual buy model calculates the quantities of parts necessary to meet a given demand with a specified confidence
- However, in order to use it you have to have demand forecasts and their associated uncertainties
- A method of data mining historical buy information has been proposed in order to establish demand uncertainties associated with lifetime and bridge buys

Stochastic Individual Buy Model:

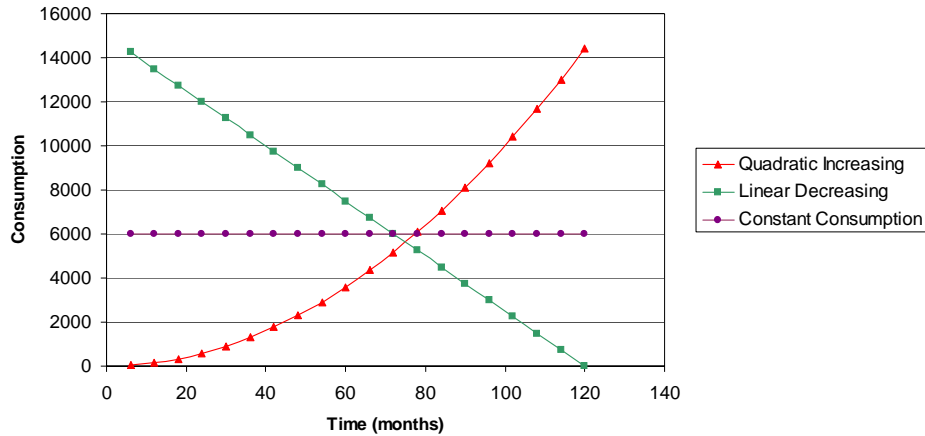
http://www.enme.umd.edu/ESCML/LTB/SimpleLTBModel_v1.1.zip

Appendix (Non-Constant Consumption)

Non-Constant Consumption

The rate at which parts are consumed by manufacturing and/or sustainment activities is usually not constant.

The consumption profile determines the rate at which parts are consumed and will alter the distribution of $\frac{\% \text{ Consumed}}{\% \text{ Time Passed}}$



Non-Constant Consumption Profile

(Algorithms)

$$\% \text{ Consumed}_i = \frac{\sum_{j=1}^i C_j}{Q_p} \times 100$$

$$\% \text{ TimePassed}_i = \frac{T_i}{L} \times 100$$

$$\left(\frac{\% \text{ Consumed}}{\% \text{ TimePassed}} \right)_i = \frac{L}{T_i Q_p} \sum_{j=1}^i C_j$$

where

i = Current time period

C_j = Parts consumed during time period j

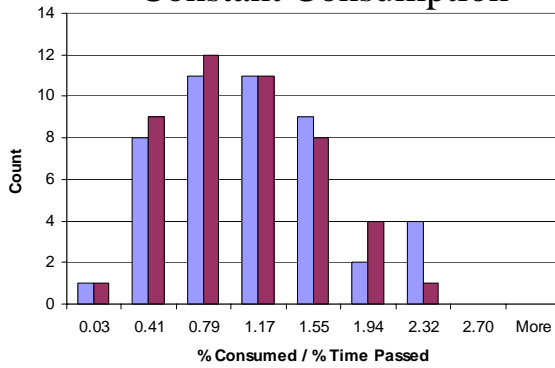
Q_p = Total projected buy quantity

T_i = Number of time periods passed

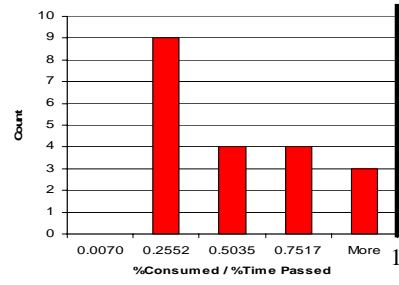
L = Length of the buy in time periods, i.e., the number of time periods until the part is no longer needed

Consumption Profiles

Constant Consumption



Quadratic Increasing Consumption



Linear Decreasing Consumption

