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EXPLORING HOW SYSTEMS AGE (AND FAIL) AND THE IMPACT ON O&S COST ESTIMATES

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AGENDA

- BACKGROUND AND INTRODUCTION
- PROBLEM IDENTIFICATION
- RELIABILITY THEORY OVERVIEW
- PROGRAM LIFECYCLE IMPACT
- APPLICATION – ANALOGOUS SYSTEM DATA
- APPLICATION – EXTRAPOLATION FROM ACTUALS
- SIMULATION OF SYSTEM
- COST ANALYSIS IMPACT
- CONCLUSIONS AND FUTURE CONSIDERATIONS
- Q&A

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BACKGROUND & INTRODUCTION

BACKGROUND

- Significantly more time is spent estimating the development and production costs of weapon systems than understanding the aging and failures for the system
- The focus of this briefing is to examine how systems age and fail at various points of the program lifecycle
- The variation in failure rates and the estimating technique used has significant impact on the estimated lifecycle cost

PROCESS FLOW

- Define the system
- Find the right data
- Parameter identification
- Simulate the system
- Analysis
- Revisit

PROBLEM IDENTIFICATION – WHY IS AGING SO DIFFICULT TO PREDICT?

COMMON CHALLENGES IMPACTING AGING PREDICTIONS

- Data Inaccuracies/Inadequacies
- Static Analysis
- Best Practices Not Applied

EXAMPLES

- Challenges of P3
- Multiple Data Collection Points
- Non-constant failure predictions - Estimates from Year 1 to Year 5 will vary (or Month 1 to Month 5)
- Let Program Lifecycle dictate estimating methodology
- It’s not always about what has failed

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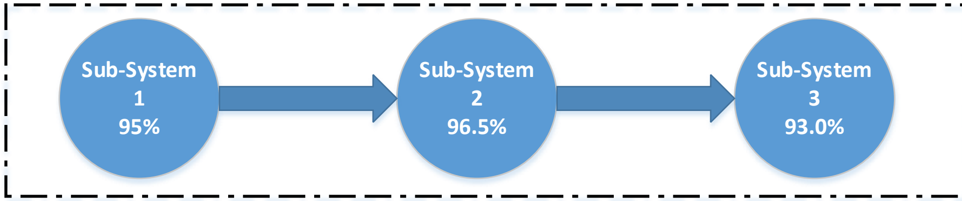
RELIABILITY OVERVIEW - SERIES VS. PARALLEL

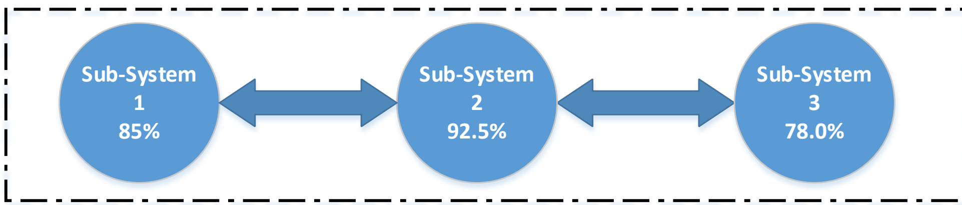
System A (Series)



95.0% * 96.5% * 93.0% = 85.3%

The overall reliability of System A is 85.3%

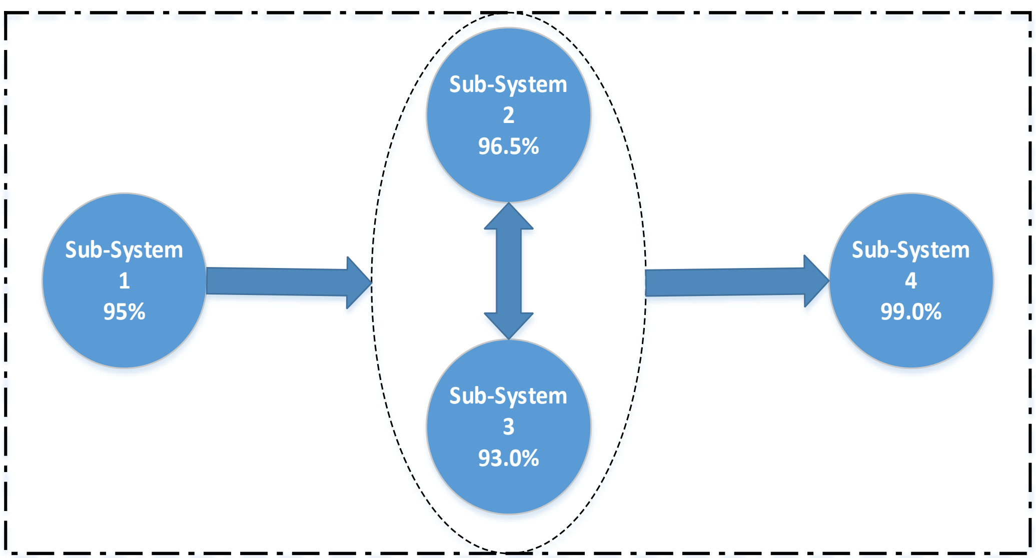
System B (Parallel)



1-((1-0.85)*(1-0.925)*(1-0.78))= 99.8%

The overall reliability of System B is 99.8%

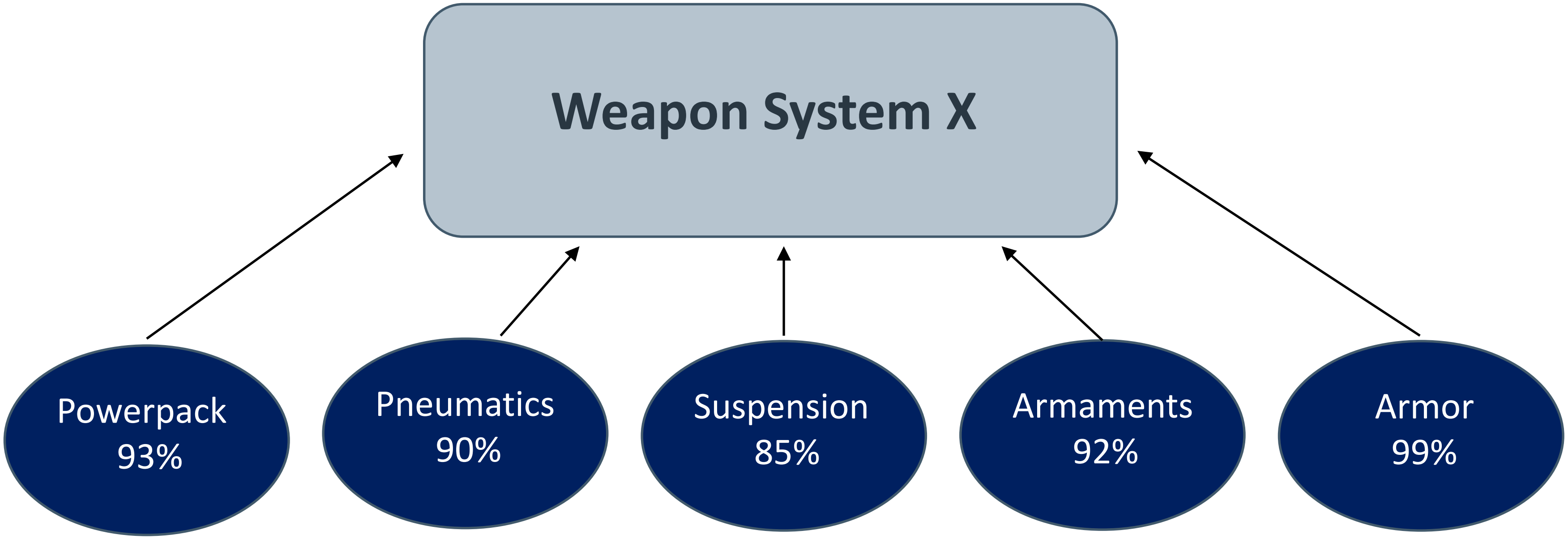
System C (Series-Parallel)



0.95*(1-((1-0.965)*(1-0.93))*0.99=93.8%

The overall reliability of System C is 93.8%

SERIES SYSTEM EXAMPLE IN CONTEXT



93% * 90% * 85% * 92% * 99% = 64.8%

The overall reliability of Weapon System X is 64.8%

WHAT REALLY HAPPENS

PROBABILITY

For cost estimating purposes, we are looking to capture likelihood of failure as a function of time (i.e. how many will fail and when)

SUBSYSTEM FAILURES

- Not cost effective to repair an entire weapon system as a result of a single sub-system failure
- Sub-system diagnostics and cost modeling are imperative to maximizing end-item availability and cost efficiency

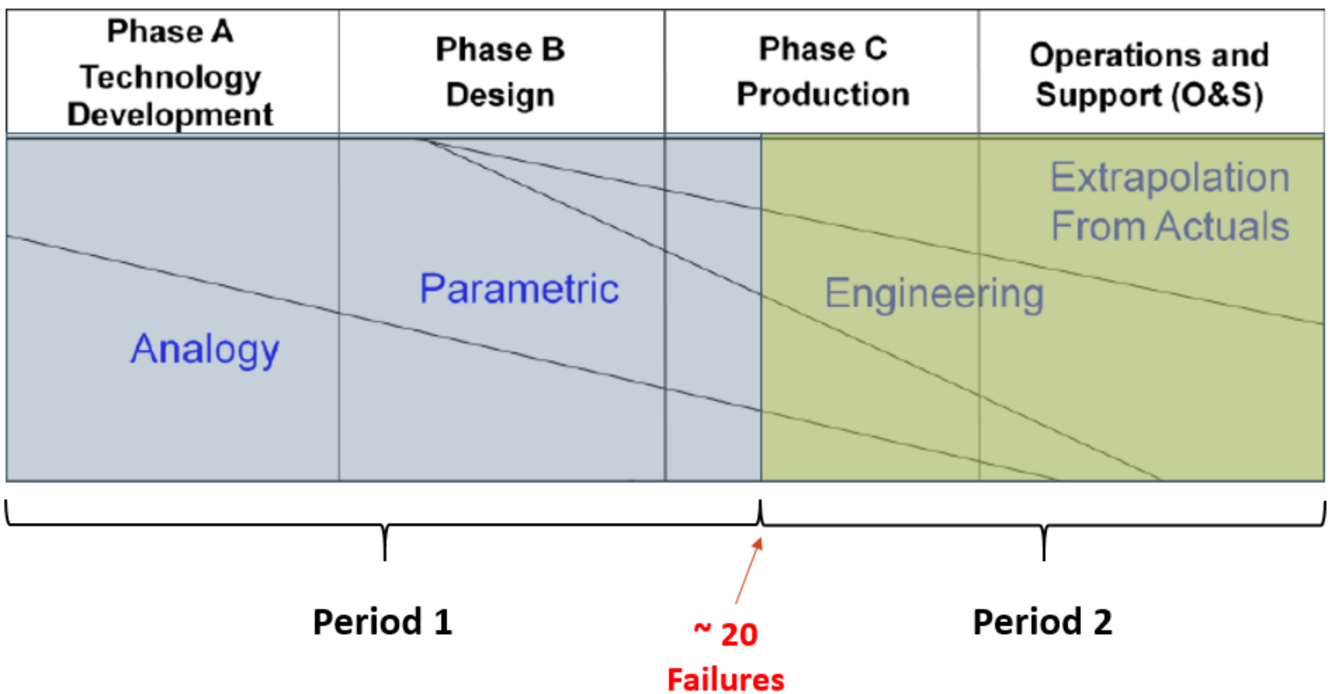
SPECIFIC FOCUS OF THIS PRESENTATION

Analyze the aging profiles and failure projections of reparable sub-systems and the impact on requirements forecasts and cost estimates

PROGRAM LIFECYCLE IMPACT

TIMING IS EVERYTHING

- The current stage of the weapon system in the program lifecycle strongly dictates the estimating methodology that should be used
- In this paper, we present a vertical line defined by a specific event (20 failures) that indicates when to change estimating methodology



ANALOGOUS SYSTEM DATA

KEY ATTRIBUTES OF ANALOGOUS SYSTEM

- Mission Objective
- Usage/OPTEMPO
- Fleet Size/Field Locations
- Maintenance Strategy
- Physical Specifications

NORMALIZATION VS. CALIBRATION

- Normalization – Adjustment of Input
  - Normalization is the adjustment of the data set to make it consistent and comparable with the end item being analyzed
  - For this study, normalization would be performed in order to achieve end item or subsystem homogeneity
- Calibration – Adjustment of Output
  - Calibration is resetting the y-intercept (or equivalently the constant term) of the CER so that it passes through a desired point (pair of coordinates).
  - Can be viewed as a “correction” to an equation or CER

ANALOGOUS SYSTEM DATA & CER

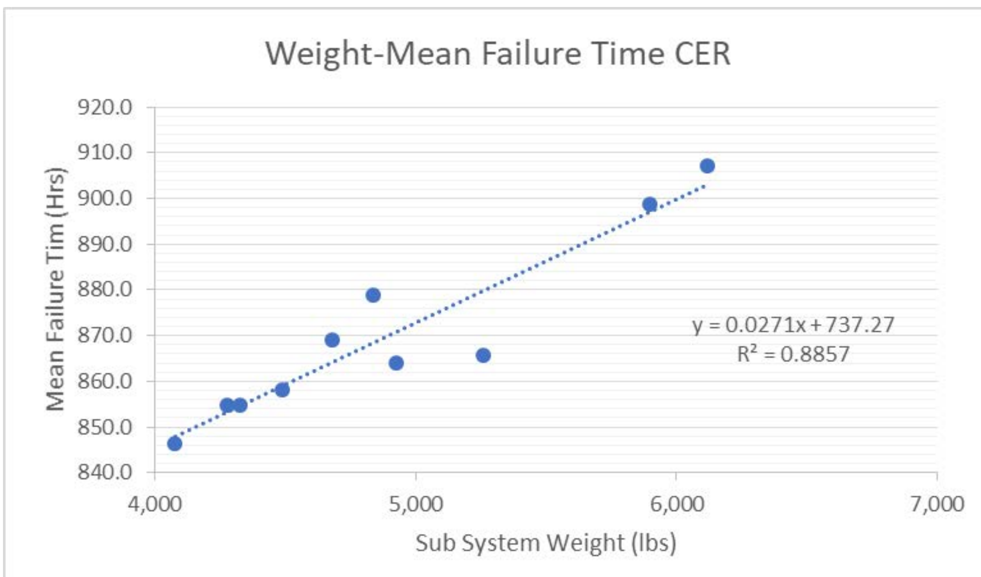
NEW SYSTEM BEING ESTIMATED

Attributes of System

Weapon System Type: Wheeled Vehicle
Period of Performance: 10 Years
Sub-System Weight: 4,500 lbs.
System Location 1 Fleet Size: 10 Units
System Location 1 OPTEMPO: 50 Hrs/Month
System Location 2 Fleet Size: 12 Units
System Location 2 OPTEMPO: 50 Hrs/Month
System Location 3 Fleet Size: 15 Units
System Location 3 OPTEMPO: 50 Hrs/Month
Total Fleet Size: 37 Units

ANALOGOUS SYSTEM DATA & CER

	Failures Observed	Mean Failure Time (Hrs)	Std. Deviation	Sub-System Weight (lbs.)
Sub-System 1	1,500	854.8	334.5	4,275.8
Sub-System 2	1,441	846.4	314.7	4,077.0
Sub-System 3	1,435	854.7	392.7	4,324.8
Sub-System 4	1,386	898.8	348.1	5,899.1
Sub-System 5	1,367	864.1	358.4	4,923.5
Sub-System 6	1,342	865.7	319.2	5,259.3
Sub-System 7	1,322	868.9	405.7	4,678.3
Sub-System 8	1,304	858.1	356.9	4,488.7
Sub-System 9	1,280	878.7	445.0	4,834.8
Sub-System 10	1,271	907.3	339.4	6,118.1



ANALOGOUS SYSTEM DATA & CER

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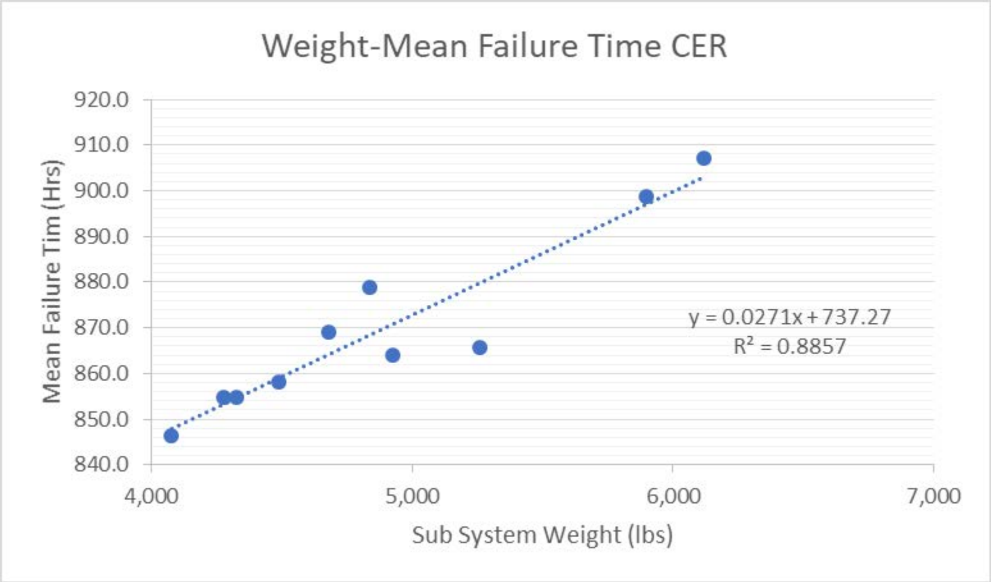

GOODNESS OF FIT & PARAMETERS

	Kolmogorov Smirnov		Anderson Darling		Chi-Squared			
Distribution	**Statistic**	**Rank**	**Statistic**	**Rank**	**Statistic**	**Rank**	**Average Rank**	**Parameters**
Weibull	**0.01864**	**1**	**0.47908**	**1**	**5.1576**	**1**	**1.0**	**α=2.6061 β=964.53**
Beta	0.01899	2	3.2993	3	9.974	2	2.3	α_1=2.4187 α_2=3.3906 a=57.231 b=1960.8
Normal	0.03638	3	2.8918	2	14.398	3	2.7	σ=356.9 μ=858.12
Gamma	0.04901	4	5.9959	4	44.948	5	4.3	α=5.7811 β=148.44
Logistic	0.05384	5	7.2435	5	36.416	4	4.7	σ=196.77 μ=858.12
Triangular	0.0609	7	12.919	6	80.07	6	6.3	m=542.04 a=57.231 b=1960.8
Rayleigh	0.06536	8	17.77	9	98.855	7	8.0	σ=684.68
Gumbel Max	0.06632	9	13.266	7	106.33	9	8.3	σ=278.27 μ=697.5
Lognormal	0.06703	10	13.755	8	99.225	8	8.7	σ=0.48781 μ=6.6517
Uniform	0.058	6	255.21	14	N/A		10.0	a=239.96 b=1476.3
Cauchy	0.09732	11	22.639	10	166.85	11	10.7	σ=230.7 μ=829.48
Gumbel Min	0.10273	12	39.048	11	133.07	10	11.0	σ=278.27 μ=1018.7
Erlang	0.16685	13	87.864	12	214.22	12	12.3	m=5 β=148.44
Exponential	0.27922	14	196	13	1043.1	13	13.3	λ=0.00117
Pareto	0.4258	16	385.98	15	2965.3	14	15.0	α=0.41991 β=71.538
Chi-Squared	0.42065	15	7875.1	16	4461.6	15	15.3	ν=858
Student's t	0.9999	17	16252	17	1.39E+08	16	16.7	ν=2

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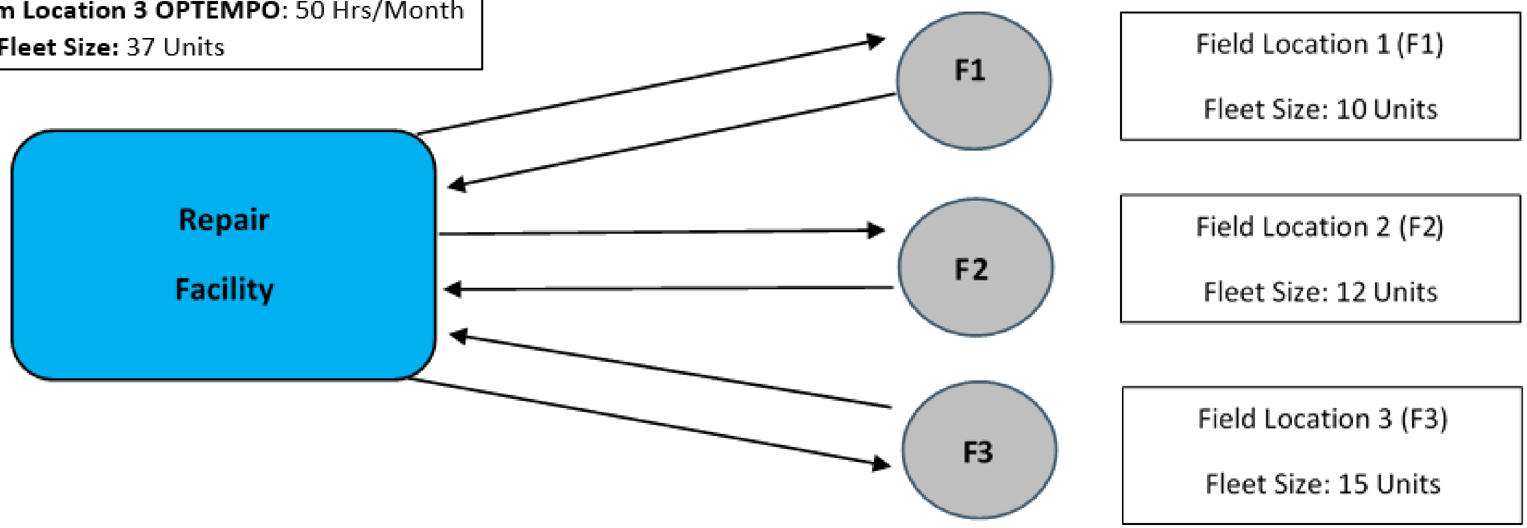
ANALOGOUS SYSTEM DATA

SYSTEM MODELING – WEAPON SYSTEM X

Objective – Identify how many of a particular sub-system will fail and when

Assumptions
Weapon System Type: Wheeled Vehicle
Period of Performance: 10 Years
Sub-System Weight: 4,500 lbs.
System Location 1 Fleet Size: 10 Units
System Location 1 OPTEMPO: 50 Hrs/Month
System Location 2 Fleet Size: 12 Units
System Location 2 OPTEMPO: 50 Hrs/Month
System Location 3 Fleet Size: 15 Units
System Location 3 OPTEMPO: 50 Hrs/Month
Total Fleet Size: 37 Units



	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Mean	9.4	26.8	26.3	25.7	25.1	26.7	25.2	27.3	25.3	25.9
Std. Dev.	2.6	4.0	4.3	3.5	3.5	3.5	3.1	3.9	3.5	3.6

EXTRAPOLATION FROM ACTUALS

INTRODUCTION TO LIFETIME & RIGHT CENSORED DATA

- Once a sub-system is integrated with an end item, its O&S lifetime begins and will continue until it experiences a distinct failure at some unknown time in the future limited by the end item's EUL

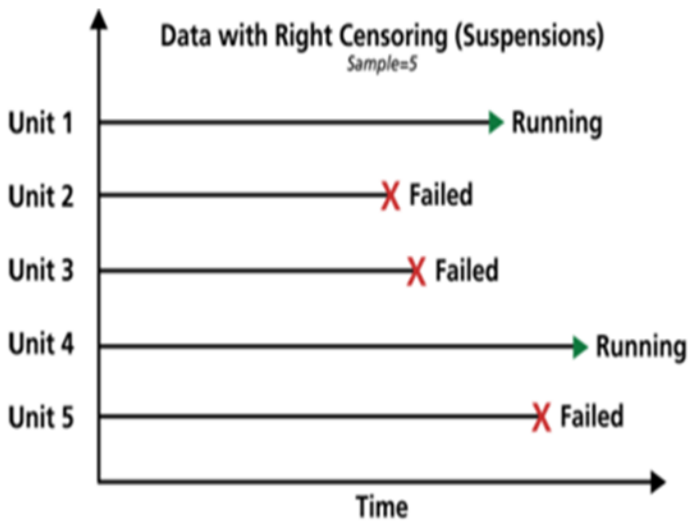
- When estimating the sub-system O&S lifetime, it is impractical to wait to create an aging profile reparable item cost estimate until a statistically significant number of failures have occurred

- When modeling a sub-system's aging profile, two types of data must be considered:
  - Data for sub-systems that have failed is known as **failure data**
  - Data for sub-systems whose failure times are unknown (i.e. fielded units that have not failed) is known as **right censored data**

EXTRAPOLATION FROM ACTUALS

MORE ON RIGHT CENSORED DATA

- With the appropriate data collection processes, right-censored data can be collected at any point in the O&S phase
- Key metrics are the current age or mileage of the sub-system and whether or not the unit has failed
- An illustration of right-censored data:



Unit Number	Hours Observed	Censored
1	10	0
2	7	1
3	8	1
4	13	0
5	12	1

EXTRAPOLATION FROM ACTUALS

PARAMETER IDENTIFICATION

- To create a model that predicts a sub-system's aging profile and time of failure, a probability of failure for any instance during the sub-system's lifetime must be calculated

- The probability (p) of observing a failure at time "t" for any unit during the system's useful life, is a function, F(t), of the given distribution's parameter "θ"

- An example would be the normal distribution with its parameters being its mean (μ), variance (σ^2) and time of failure (x), seen below:

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(x-\mu)^2}{2\sigma^2}}$$

EXTRAPOLATION FROM ACTUALS

MAXIMUM LIKELIHOOD ESTIMATION (MLE)

- In practice, θ is unknown before failure data is collected but it can be estimated using the Maximum Likelihood Estimation (MLE)

- MLE works by calculating the most accurate θ by maximizing the probability of observing each failure in the data according to the likelihood equation

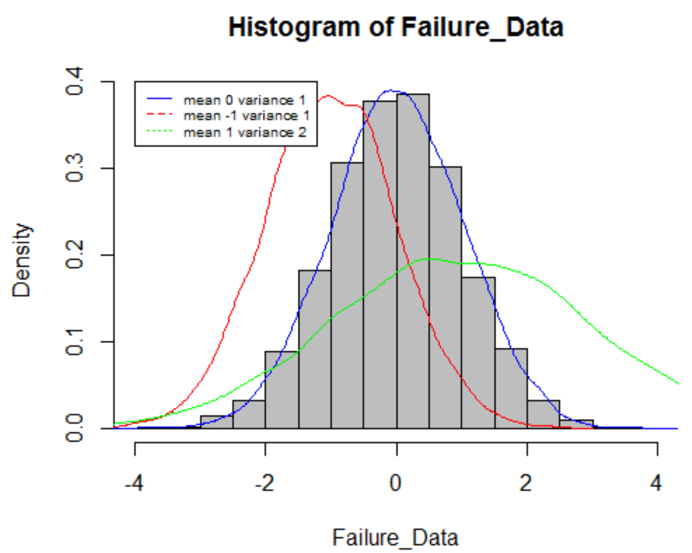
- The likelihood equation (seen below) quantifies the probability of observing the failures actually occurring at their given hours according to the estimated parameters θ, of the distribution

$$L(\theta) = \mathcal{C} \prod_{i=1}^{n} L_i(\theta; \mathrm{data}_i)$$

EXTRAPOLATION FROM ACTUALS

MAXIMUM LIKELIHOOD ESTIMATION (MLE) - EXAMPLE

- Probability distributions, like the Normal distribution, get their shape from their parameters μ and σ^2
- MLE utilizes the likelihood equation to find the most accurate parameters according to the failure data observed



EXTRAPOLATION FROM ACTUALS

MAXIMUM LIKELIHOOD ESTIMATION – RIGHT CENSORED (MLE-RC)

- MLE R-C takes advantage of the data that has yet to fail to build a more accurate aging profile and predictive failure model
- MLE R-C is calculated the same as traditional MLE except for one key step:
    - MLE R-C likelihood equation maximizes both the likelihood of observing all the failures (δ =1) and the likelihoods of all the right censored data points (δ =0) not failing up until their current age

$$L(\boldsymbol{\theta}) = \prod_{i=1}^{n} \{f(t_i; \boldsymbol{\theta})\}^{\delta_i} \{1 - F(t_i; \boldsymbol{\theta})\}^{1-\delta_i},$$

EXTRAPOLATION FROM ACTUALS

DISTRIBUTION FITTING/BEST FIT IDENTIFICATION

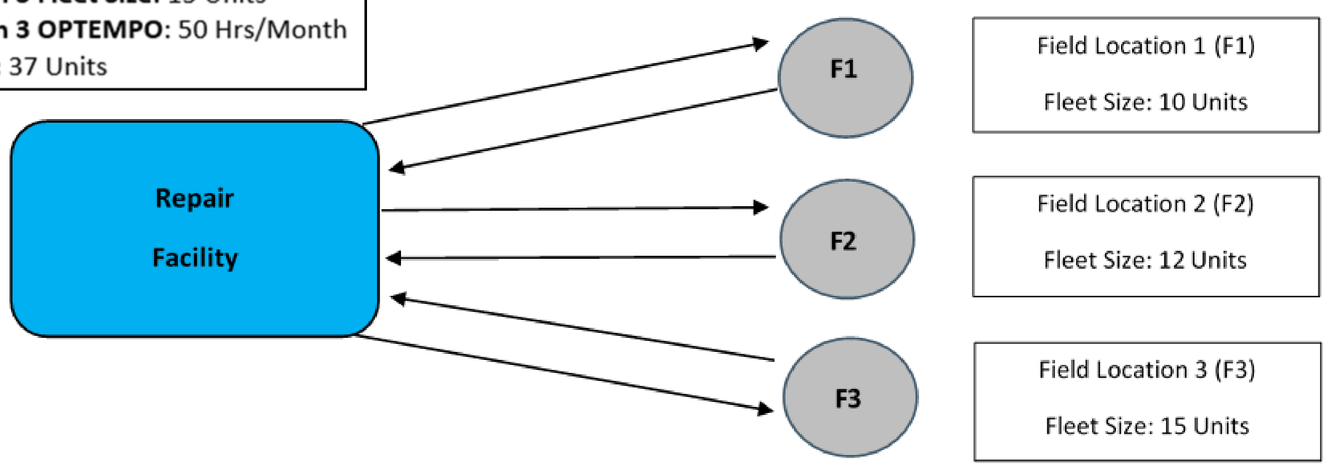
- The underlying distribution of lifetime data is unknown before it is analyzed, so a variety of distributions have to be fit via right censored MLE to best model the weapon system
- To evaluate how well of a fit the distributions are to the data, goodness of fit (GOF) tests are used by measuring how close the actual lifetime data is to the theoretical distribution
- Our data did not pass GOF tests for the normal distribution or exponential distribution but did fit very well to the Weibull distribution

SIMULATION OF SYSTEM

SYSTEM MODELING – WEAPON SYSTEM X

Objective – Identify how many of a second sub-system of Weapon System X will fail and when using MLE and MLE-RC

Assumptions
Weapon System Type: Wheeled Vehicle
Period of Performance: 10 Years
Sub-System Weight: 4,500 lbs.
System Location 1 Fleet Size: 10 Units
System Location 1 OPTEMPO: 50 Hrs/Month
System Location 2 Fleet Size: 12 Units
System Location 2 OPTEMPO: 50 Hrs/Month
System Location 3 Fleet Size: 15 Units
System Location 3 OPTEMPO: 50 Hrs/Month
Total Fleet Size: 37 Units



SIMULATION OF SYSTEM

MLE-RC VS. MLE - RESULTS

Total Failures By Year for All Sites with MLE-RC (30 Trials)									
Censoring Rate	**90%**	**80%**	**70%**	**60%**	**50%**	**40%**	**30%**	**20%**	**10%**
Shape	**4.5**	**4.08**	**4.02**	**4.19**	**4.18**	**4.21**	**4.22**	**4.28**	**4.2**
Scale	**2140**	**1884**	**1711**	**1585**	**1503**	**1438**	**1387**	**1344**	**1306**
Year 1	0.1	0.6	0.4	0.5	0.9	0.9	1.2	0.9	1.6
Year 2	2.4	5.2	7.8	8.9	12.0	13.7	14.3	16.0	18.4
Year 3	11.9	15.4	18.1	21.1	20.7	21.8	21.9	22.2	20.6
Year 4	16.4	15.9	15.0	12.9	13.3	13.3	14.7	14.8	17.5
Year 5	9.7	10.9	11.6	15.0	17.6	18.3	18.6	21.0	20.5
Year 6	8.9	13.0	16.3	17.0	15.8	16.7	16.2	16.1	17.0
Year 7	13.2	13.5	13.6	14.0	15.8	17.0	18.4	19.3	19.8
Year 8	12.0	12.7	13.2	15.1	17.0	17.2	17.5	17.7	18.1
Year 9	10.8	13.5	15.6	16.8	15.4	16.4	17.5	18.3	19.0
Year 10	11.6	12.0	14.4	14.5	16.2	17.3	18.5	18.4	18.6
Total	97.0	112.7	125.9	135.6	144.7	152.5	158.8	164.6	171.1

Total Failures By Year for All Sites with MLE (30 Trials)									
Censoring Rate	**90%**	**80%**	**70%**	**60%**	**50%**	**40%**	**30%**	**20%**	**10%**
Shape	**4.8**	**4.04**	**4.05**	**4.34**	**4.21**	**4.24**	**4.16**	**4.21**	**4.19**
Scale	**1292**	**1268**	**1264**	**1264**	**1270**	**1273**	**1276**	**1281**	**1272**
Year 1	1.2	1.6	1.8	1.5	1.4	2.0	1.1	1.0	1.7
Year 2	17.5	18.9	18.4	19.1	18.1	17.5	20.1	18.1	18.2
Year 3	21.4	20.9	20.9	20.8	21.2	21.5	19.7	21.8	21.1
Year 4	17.2	18.5	19.4	18.5	17.4	18.1	18.2	17.6	17.9
Year 5	20.7	20.6	19.2	19.9	20.1	20.0	20.5	20.7	20.3
Year 6	17.9	18.4	19.2	18.6	18.9	19.1	17.8	17.2	18.4
Year 7	19.2	19.6	19.7	20.4	19.6	19.5	21.5	19.3	19.4
Year 8	18.5	19.2	19.7	19.2	18.9	18.7	18.0	18.6	19.4
Year 9	18.8	19.7	18.8	19.4	19.4	19.2	19.8	19.0	18.9
Year 10	18.7	18.2	19.9	19.1	19.4	19.1	18.9	19.4	19.1
Total	171.1	175.5	176.9	176.3	174.5	174.6	175.6	172.7	174.4

SIMULATION OF SYSTEM

IDENTIFYING WHEN RIGHT-CENSORED INFORMATION NO LONGER IMPACTS FAILURE PREDICTION ACCURACY

$$t = \frac{(\overline{x}_1 - \overline{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Data is 60% Censored

t-Test: Two-Sample Assuming Unequal Variances

	MLE-RC	*MLE*
Mean	13.56333	17.63333333
Variance	30.82974	32.80938272
Observations	10	10
Hypothesized Mean Difference	0	
df	18	
t Stat	-1.61336	
P(T<=t) one-tail	0.06203	
t Critical one-tail	1.734064	
P(T<=t) two-tail	0.124059	
t Critical two-tail	2.100922	

Data is 70% Censored

t-Test: Two-Sample Assuming Unequal Variances

	MLE-RC	*MLE*
Mean	12.58667	17.69
Variance	26.2319	31.75359
Observations	10	10
Hypothesized Mean Difference	0	
df	18	
t Stat	-2.11931	
P(T<=t) one-tail	0.024114	
t Critical one-tail	1.734064	
P(T<=t) two-tail	0.048228	
t Critical two-tail	2.100922	

SIGNIFICANCE OF THE 20TH FAILURE

PREVIOUS RESEARCH ON IMPACT OF RIGHT CENSORED DATA

$$\text{RRMSE} = \frac{\sqrt{SD(\theta)^2 + Bias\ (\theta)^2}}{\vartheta}$$

$\theta =$ estimated result of the concerned parameter;
$\vartheta =$ true value of the concerned parameter

RRMSE of β	*Censoring Rate*			
	95%	*90%*	*85%*	*80%*
<0.25	400	200	150	100
Corresponding Minimum No. of Failures				
	20	*20*	*22.5*	*20*
Corresponding RRMSE of η				
	0.1391	0.1030	0.0808	0.0655

Reference - Li, C., Wang, Z., Zhou, D. (2013) Data Requisites for Transformer Statistical Lifetime Modelling—Part I: Aging-Related Failures. IEEE Transactions on Power Delivery, Volume 28 (No. 3), Pages 1750-1757.

SIMULATION OF SYSTEM

COST IMPACT

- Assume a repair cost of $150,000 per failure
- The table below shows the difference in the mean predicted failures by year and censoring rate for MLE and MLE-RC and the cost impact
- MLE greatly overestimates cost for high censoring rates

	Difference in Estimated Failures (μ_{MLE} - μ_{MLE-RC})								
Censoring Rate	**90%**	**80%**	**70%**	**60%**	**50%**	**40%**	**30%**	**20%**	**10%**
Year 1	1.0	1.0	1.4	1.0	0.6	1.1	-0.1	0.1	0.1
Year 2	15.2	13.6	10.6	10.2	6.0	3.8	5.8	2.1	-0.2
Year 3	9.5	5.5	2.8	-0.3	0.4	-0.3	-2.2	-0.4	0.5
Year 4	0.8	2.6	4.4	5.6	4.1	4.8	3.5	2.8	0.4
Year 5	11.0	9.7	7.6	4.9	2.6	1.7	1.9	-0.3	-0.2
Year 6	9.0	5.4	3.0	1.6	3.1	2.4	1.6	1.1	1.4
Year 7	6.0	6.1	6.0	6.4	3.8	2.5	3.1	0.0	-0.4
Year 8	6.5	6.4	6.5	4.0	1.8	1.5	0.5	0.9	1.3
Year 9	8.0	6.2	3.2	2.6	4.0	2.8	2.3	0.7	-0.1
Year 10	7.1	6.2	5.5	4.6	3.3	1.8	0.4	1.0	0.5
Net Difference	74.1	62.8	51.0	40.7	29.7	22.1	16.8	8.1	3.3
Cost Differential	$11,115,000	$9,420,000	$7,655,000	$6,105,000	$4,460,000	$3,310,000	$2,520,000	$1,210,000	$490,000

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COST ANALYSIS IMPACT

5.03 – DEPOT-LEVEL REPARABLES (SPARES)

- Requirements first, cost impact second
- Analysis can be highly sensitive to usage/OPTEMPO
- Field location variables must be considered
- Maintenance strategy must be very well defined

OTHER IMPACTS

- Proper identification of parameters can help predict optimal fleet size
- Reduction in downtime or non-value added time
- Bayesian applications can promote root-cause analysis and assist in ECP development

CONCLUSIONS AND FUTURE CONSIDERATIONS

CONCLUSIONS

- Where a weapon system is during its program lifecycle will strongly dictate the best methodology for estimating how that weapon system and its sub-systems will age and fail
- Understanding of the weapon system's maintenance strategy is key
- Accuracy of the aging model may be improved by considering the right-censored data
- Rate of improvement is defined by the censoring rate of the data

FUTURE CONSIDERATIONS

- Impact of failure mode tracking and integration into model
- Proper integration and analysis can promote strategic cost and programmatic decision-making

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Q&A