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Non-Operational Stockpile Reliability Prediction Methods Using Logistic Regression Techniques

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Summary

- This paper provides an approach and documents the results of an ongoing case study that uses binary logistic regression (BLR) techniques (both classical and Bayesian) to assess system failures uncovered following non-operating dormant periods and non-operating transportation.
- This new storage reliability prediction method leverages predecessor system data, which is similar to new systems being designed, and assesses the differences between the predecessor systems and that of the new system design.
- This new prediction method using empirical storage reliability data results in a series of reliability curves that show reliability function changing over time.
- This result is very different from previous prediction methods.
  - Instead of a prediction resulting in a single point estimate with assumptions of a constant failure rate and an exponential distribution as the probability density function (pdf), the new method determines the best fit of a distribution to the data.
  - Using the empirical data from the field sources analyzed with the BLR approaches provides higher accuracy in new system design reliability prediction methods compared to previous methods using outdated military reliability prediction standards.
- Standard data format was used to collect failure data from various field sources, and notional data analysis and resulting curves to support the accuracy of the new prediction method.
- Reliability prediction curves resulting from BLR analysis using the logit function are provided.

The Challenge

- An important reliability issue is how to develop a predictive model to estimate how many units of any given product will fail over a particular period of time
- The challenge of developing a non-operational stockpile reliability prediction is:
  - the dependence on availability of empirical evidence composed of failure (degradation) mechanisms from detailed root cause analysis
  - an understanding of the system storage environment.
  - Field failure data can be misleading due to the fact that root cause diagnosis of field failures may not be available.

Storage Reliability Predictive Model Challenge

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Environmental Profile

- Non-operational Storage Reliability represents the unpowered state of a product that is deployed and occasionally tested using Built In Test (BIT) or external test support equipment by a customer in the field or fleet.
  - A typical dormant stockpile environment will be an unpowered, benign environment for a large percentage of the time in storage with excursions at temperature and humidity extremes, and multiple packaging, handling, shipping and transportation (PHS&T) cycles during deployment.
  - Some systems are often stored in a shipping and storage container that may be stored under environmental conditions ranging from open, unsheltered areas with diurnal temperature cycles to environmentally controlled facilities

Data Collection

- The data requirements included part lists/BOMs, schematics, assembly drawings, part drawings, quantities of systems in the field, dates of systems delivered to the field, durations of systems in the field, field failure data, and failure data from various internal and external sources and databases, and published literature.
- Various systems with field surveillance programs were considered and the first choices in the selection process were those programs that maintained complete and accurate field Failure Reporting Analysis and Corrective Action System (FRACAS) data.
- Following data collection activities, data correlation, data categorization, and data summary occurred.
- The customer may choose to have the product repaired (parts removed and replaced) and returned to the field without root cause diagnosis being performed.

Must Have Covariate Data

Data Collection Format

- A standard format of the system data was developed for ease of data collection and analysis.
- Both non-operational and operational system failures were considered in assessing the presence of wear-out mechanisms and degradation.
- There were 7 critical fields that defined the pedigree of the records, dates and status at time of testing or inspection.
- These fields were:
  - Product name
  - Product type
  - Product serial number
  - Delivery date
  - Test date
  - Inspection date
  - Pass/Fail status

Logistic Regression

- In statistics, logistic regression (sometimes called the logistic model or logit model) is used for prediction of the probability of occurrence of an event by fitting data to a logit function logistic curve
- It is a generalized linear model used for binomial regression.
- The objective is to use AGE as the regression variable, where AGE = weeks since left factory, CC time is captive carry time under wing of aircraft, Storage # = # of different storage facilities since leaving the factory.
- There is a dilemma that occurs when using the "AGE" of a system as a surrogate for time-to-failure (TTF).
  - Typically at some designated interval a certain number of supposedly randomly chosen systems of a given type are pulled from storage and a test or inspection is performed.
  - The actual AGE of the system at the time a failure is detected in test would not be a correct failure TTF
  - The system probably experienced a physical degradation wearout mechanism (failure condition) would most likely have occurred sometime prior to the test or the BIT, after the time of the previous BIT
  - The test probably would not have induced a failure, but simply detected a failure that was already precipitated
- Binary Logistic Regression (BLR) is the binary "censored" version of the Logistic Regression.

AGE is a covariate

BLR Model

- An alternative model treats the pass/fail or binary data directly (e.g., r=1 (pass) or a r=0 (fail))
- Use AGE, and possibly other factors, called covariates, in formulating a regression equation for the reliability.
- Since the data is either a pass or fail, and the reliability is a probability bounded between 0 and 1, we need a mapping (called a link function) between the response (reliability) and the covariates. This mapping is in the form of a function, g(R), where: R = reliability = Pr{r=1}.
  - $g(R)=\text{logit}(R)=\ln[R/(1-R)] = b_0 + b_1X_1 + b_2X_2 +\ldots+ b_{11}X_1^2 + b_{12}X_1X_2+ \ldots$ + higher order terms = $\mathbf{X\ b}$
  - Inverting the above equation $R = 1 / [1+ \exp\{- \mathbf{X\ b}\}]$
- The BLR techniques were developed and implemented on a non-operational stockpile reliability prediction project, which demonstrated the capability to meet the challenge.

Logit Analysis

- How is a model built? Consider the following model.

  $\ln[R/(1-R)]=\beta_0+\beta_1*AGE+\beta_2*CC+\beta_3*STORAGE$

  or

  $R = 1 / [1 + \exp\{-(\beta_0+\beta_1*AGE+\beta_2*CC+\beta_3*STORAGE)\}]$

- Performing a classical BLR analysis uses data to find estimators for the coefficients $\{ \beta_0,\beta_1,\beta_2,\beta_3\}$ using the logit function produces reliability prediction curves as shown on next chart.
- Bayesian BLR reliability uses distribution functions for the coefficients $\{f_0(\beta_0),f_1(\beta_1),f_2(\beta_2),f_3(\beta_3)\}$ and using Markov Chain Monte Carlo (MCMC) techniques to produce a distribution function for R

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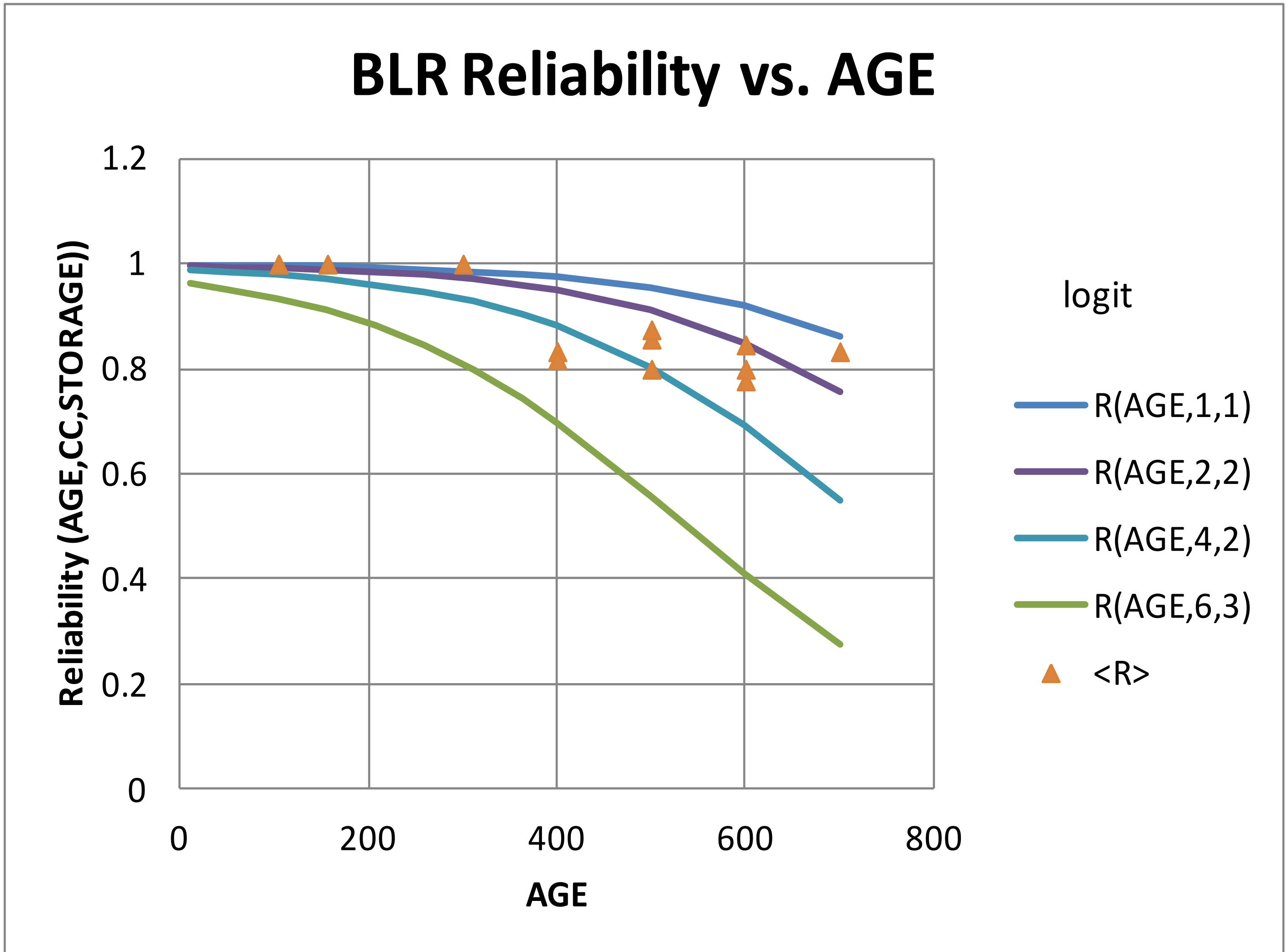
Notional Data Set to Calculate R

Test No.	r (0 or 1)	AGE (Weeks)	CC time (hours)	Storage No,	<R>
1	1	104	2	1	1
2	1	156	2	1	1
3	1	104	1	1	1
4	1	300	4	2	1
5	0	500	4	2	0.8
6	1	400	2	1	0.833333
7	1	500	2	2	0.857143
8	1	500	6	3	0.875
9	0	600	4	2	0.777778
10	1	600	2	1	0.8
11	1	400	4	2	0.818182
12	1	700	3	2	0.833333
13	1	600	4	1	0.846154

BLR Curves – R output against one covariate



Reliability varies with covariates!

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Handbook

- An initial storage reliability handbook, based on three system programs was developed in 2011 that describes the methodologies used to develop reliability prediction models, generated from system-level empirical field and fleet test and inspection data across the programs' systems lifecycle.
- This handbook will be used to improve storage reliability assessment accuracy using a methodology based on the BLR model to predict the future storage reliability of systems with a higher degree of accuracy from the previous method.
- Additional data collection and analysis are in progress to add seven more system programs to the database.

Handbook would be useful

Recommendations

- New sets of data from current programs need to be taken to allow for validation of the proposed models
- Models should be used to predict future performance outcomes, determine best fits of data to models, and from this, the better model(s) will survive
- Continuous model updates need to occur using data accumulated over the last 3-5 years to refresh the models
  - Without accumulation of fresh data sets, we could not determine the best model and would instead perform a form of curve fitting (e.g., double exponential moving average), and live with very high variability in reliability predictions
- It is not possible to compare the outcome of a multivariate logistics model with a single number calculated, such as the ratio of (# systems passed testing) vs (# systems tested), as this average value has no information that distinguishes one system from another

References

- Raytheon Missile Systems Storage Reliability Design Guide, Raytheon Proprietary
- RAMS 2013 paper and presentation, titled: “Models and Methods for Determining Storage Reliability”, URL: http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=6532083&url=http%3A%2F%2Fieeexplore.ieee.org%2Fiel7%2F6523362%2F6531927%2F06532083.pdf%3Farnumber%3D6532083

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