Statistical Model Selection for TID Hardness Assurance

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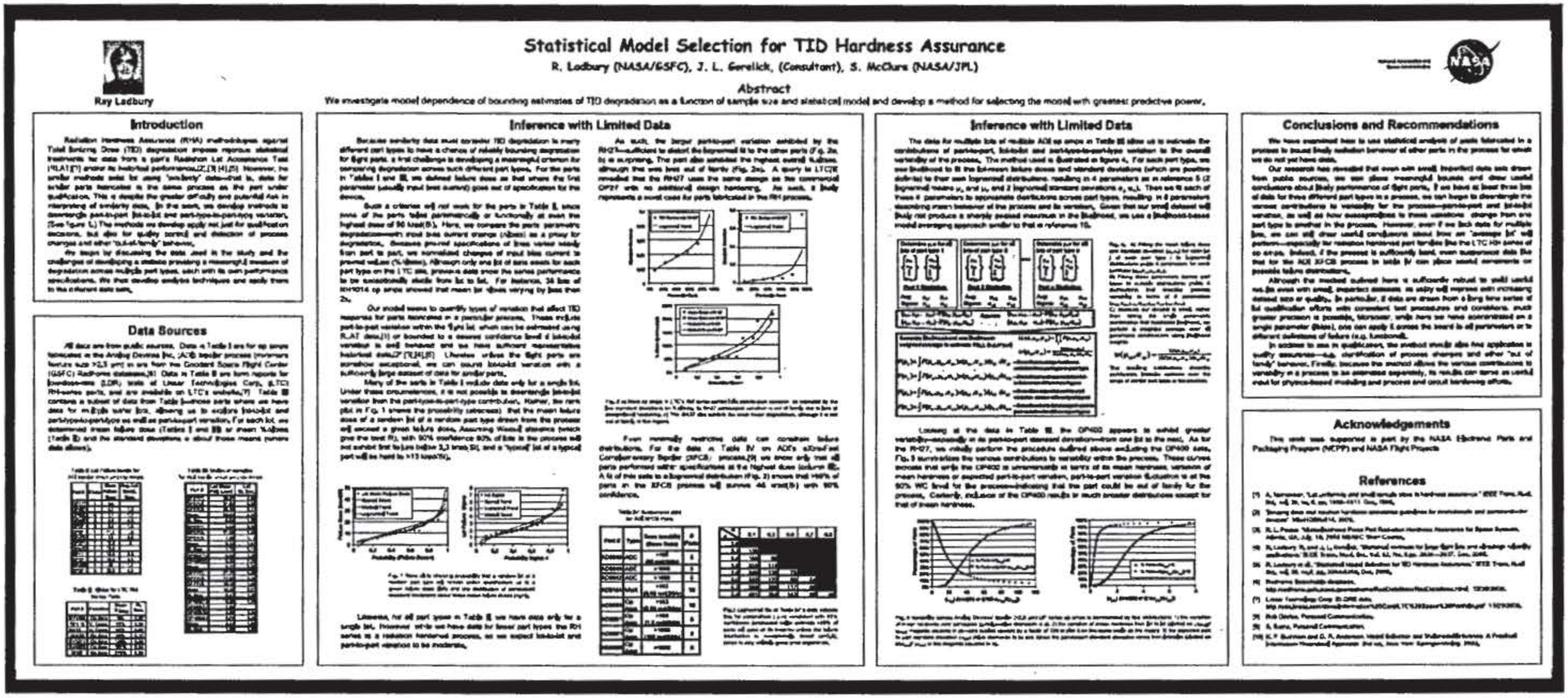
Abstract

We investigate model dependence of bounding estimates of TID degradation as a function of sample size and statistical model and develop a method for selecting the model with greatest predictive power.



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Introduction

Radiation Hardness Assurance (RHA) methodologies against Total Ionizing Dose (TID) degradation impose rigorous statistical treatments for data from a part's Radiation Lot Acceptance Test (RLAT)[1] and/or its historical performance.[2],[3],[4],[5] However, no similar methods exist for using "similarity" data—that is, data for similar parts fabricated in the same process as the part under qualification. This is despite the greater difficulty and potential risk in interpreting of similarity data. In this work, we develop methods to disentangle part-to-part, lot-to-lot and part-type-to-part-type variation. (See figure 1.) The methods we develop apply not just for qualification decisions, but also for quality control and detection of process changes and other "out-of-family" behavior.

We begin by discussing the data used in the study and the challenges of developing a statistic providing a meaningful measure of degradation across multiple part types, each with its own performance specifications. We then develop analysis techniques and apply them to the different data sets.

Data Sources

All data are from public sources. Data in Table I are for op amps fabricated in the Analog Devices Inc. (ADI) bipolar process (minimum feature size >2.5 μm) in are from the Goddard Space Flight Center (GSFC) Radhome database.[6] Data in Table II are form reports for low-dose-rate (LDR) tests of Linear Technologies Corp. (LTC) RH-series parts, and are available on LTC's website.[7] Table III contains a subset of data from Table I—those parts where we have data for multiple wafer lots, allowing us to explore lot-to-lot and part-type-to-part-type as well as part-to-part variation. For each lot, we determined mean failure dose (Tables I and III) or mean %ΔIbias (Table II) and the standard deviations σ about those means (where data allows).

Table I: Lot Failure levels for ADI bipolar (>2.5 μm) Op Amps

Part #	# lots	Mean Failure Dose	Avg. Lot Stand. Dev.
OP177	1	2.5	
OP497	1	5.7	1.2
OP400	4	7.1	1.7
OP467	2	9.2	4.5
OP07	3	9.4	1.8
OP97	1	11.1	1.5
OP270	1	12	2.8
OP271	1	12.5	2
OP470	1	12.5	
OP11	1	12.6	2.3
OP77	3	16.4	2.3
OP200	1	22	1.7
OP27	3	29.5	4.3

Table II: ΔIbias for LTC RH Series Parts

Part #	Function	Mean D Ibias	St. Dev.
RH1499	Op Amp	5%	0.02
RH119	V. Comp.	45%	0.04
RH1011	V. Comp.	56%	0.03
RH108	Op Amp	56%	0.10
RH1014	Op Amp	126%	0.06
RH1078	Op Amp	191%	0.04
RH27	Op Amp	215%	0.76

Table III: Multi-Lot samples for ADI bipolar (>2.5 μm) Op Amps

Part #	Lot Mean Fail. Level	Lot St. Dev.
OP27(1)	39.00	2.80
OP27(2)	21.00	5.00
OP27(3)	28.50	5.07
Mean	29.50	4.29
St. Dev.	9.04	1.29
OP07(1)	9.50	3.20
OP07(2)	11.00	1.30
OP07(3)	7.60	1.10
Mean	9.37	1.87
St. Dev.	1.70	1.16
OP467(1)	9.90	1.30
OP467(2)	8.50	7.70
Mean	6.70	3.39
OP77(1)	21.19	4.08
OP77(2)	17.50	2.20
OP77(3)	10.50	1.60
Mean	16.40	2.63
St. Dev.	5.43	1.29
OP400(1)	8.00	1.76
OP400(2)	2.50	
OP400(3)	4.69	3.04
OP400(4)	6.08	0.28
Mean	4.42	1.66
St. Dev.	1.80	1.96

Inference with Limited Data

Because similarity data must consider TID degradation in many different part types to have a chance of reliably bounding degradation for flight parts, a first challenge is developing a meaningful criterion for comparing degradation across such different part types. For the parts in Tables I and III, we defined failure dose as that where the first parameter (usually input bias current) goes out of specification for the device.

Such a criterion will not work for the parts in Table II, since none of the parts failed parametrically or functionally at even the highest dose of 50 krad(Si). Here, we compare the parts' parametric degradation—with input bias current change (ΔIbias) as a proxy for degradation. Because pre-rad specifications of Ibias varied widely from part to part, we normalized changes of input bias current to pre-rad values (%ΔIbias). Although only one lot of data exists for each part type on the LTC site, previous data show the series performance to be exceptionally stable from lot to lot. For instance, 38 lots of RH1014 op amps showed that mean lot ΔIbias varying by less than 2x.

Our model seeks to quantify types of variation that affect TID response for parts fabricated in a particular process. These include part-to-part variation within the flight lot, which can be estimated using RLAT data,[1] or bounded to a desired confidence level if lot-to-lot variation is well behaved and we have sufficient representative historical data.[2],[3],[4],[5] Likewise, unless the flight parts are somehow exceptional, we can bound lot-to-lot variation with a sufficiently large dataset of data for similar parts.

Many of the parts in Table I include data only for a single lot. Under these circumstances, it is not possible to disentangle lot-to-lot variation from the part-type-to-part-type contribution. Rather, the rank plot in Fig. 1 shows the probability (abscissa) that the mean failure dose of a random lot of a random part type drawn from the process will exceed a given failure dose. Assuming Weibull statistics (which give the best fit), with 90% confidence 90% of lots in the process will not exhibit first failure below 3.3 krad(Si), and a "typical" lot of a typical part will be hard to >13 krad(Si).

As such, the larger part-to-part variation exhibited by the RH27—sufficient to distort the lognormal fit to the other parts (Fig. 2a, b) is surprising. The part also exhibited the highest overall %ΔIbias, although this was less out of family (Fig. 2c). A query to LTC[8] revealed that the RH27 uses the same design as the commercial OP27 with no additional design hardening. As such, it likely represents a worst case for parts fabricated in the RH process.

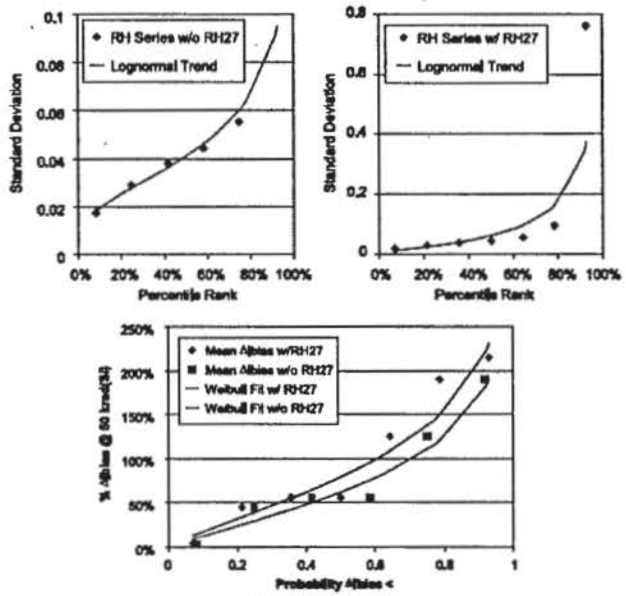

Fig. 2 a) Most op amps in LTC's RH series exhibit little part-to-part variation, as indicated by the low standard deviations on %ΔIbias. b) RH27 part-to-part variation is out of family due to lack of design-level hardening. c) The RH27 also exhibits the most mean degradation, although it is not out of family in this regard.

Even minimally restrictive data can constrain failure distributions. For the data in Table IV on ADI's eXtra-Fast Complementary Bipolar (XFCB) process,[9] we know only that all parts performed within specifications at the highest dose (column III).

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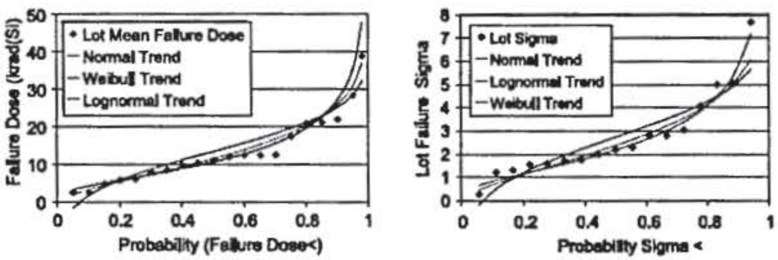

Fig. 1 Rank plots showing probability that a random lot of a random part type will remain within specification up to a given failure dose (left) and the distribution of part-to-part standard deviations about those mean failure doses (right).

Likewise, for all part types in Table II, we have data only for a single lot. However, while we have data for fewer part types, the RH series is a radiation hardened process, so we expect lot-to-lot and part-to-part variation to be moderate.

Even minimally restrictive data can constrain failure distributions. For the data in Table IV on ADI's eXtra-Fast Complementary Bipolar (XFCB) process,[9] we know only that all parts performed within specifications at the highest dose (column III). A fit of this data to a lognormal distribution (Fig. 3) shows that >99% of parts in the XFCB process will survive 45 krad(Si) with 90% confidence.

Tablo IV: Suspension data for ADI XFCB Parts

Part #	Type	Dose krad(Si) (Dose Rate)	# Parts
AD6640	ADC	>100 (50 rad(Si)/s)	5
AD6640	ADC	>1000	5
AD9042	ADC	>1000	5
AD8184	MUX	>103 (0.06 rad(Si)/s)	10
AD8063	Op Amp	>103 (0.06 rad(Si)/s)	10
AD8001	Op Amp	>100 (1.5 rad(Si)/s)	5
AD8001	Op Amp	>1000 (150 rad(Si)/s)	5
AD8009	Op Amp	>1000	5

μ \ σ	0.1	0.3	0.5	0.7	0.9
5.0					
5.2	136				
5.4	166	93			
5.6	203	114			
5.8	248	139	78		
6.0	302	170	96	54	
6.2	369	208	117	66	
6.4	451	254	143	80	45

Fig.3 Lognormal fits of Table IV"s data indicate that for parameters (μ,σ) consistent with 90% confidence (unshaded cells) estimate >99% of parts will pass at 45 krad(Si) unless the failure distribution is exceptionally broad (σ>0.9), which is very unlikely given prior experience.

Inference with Limited Data

The data for multiple lots of multiple ADI op amps in Table III allow us to estimate the contributions of part-to-part, lot-to-lot and part-type-to-part-type variation to the overall variability of the process. The method used is illustrated in figure 4. For each part type, we use likelihood to fit the lot-mean failure doses and standard deviations (which are positive definite) to their own lognormal distributions, resulting in 4 parameters as in reference 5 (2 lognormal means μ_μ and μ_σ and 2 lognormal standard deviations σ_μ σ_σ). Then we fit each of these 4 parameters to appropriate distributions across part types, resulting in 8 parameters describing mean behavior of the process and its variation. Given that our small dataset will likely not produce a sharply peaked maximum in the likelihood, we use a likelihood-based model averaging approach similar to that in reference 10.

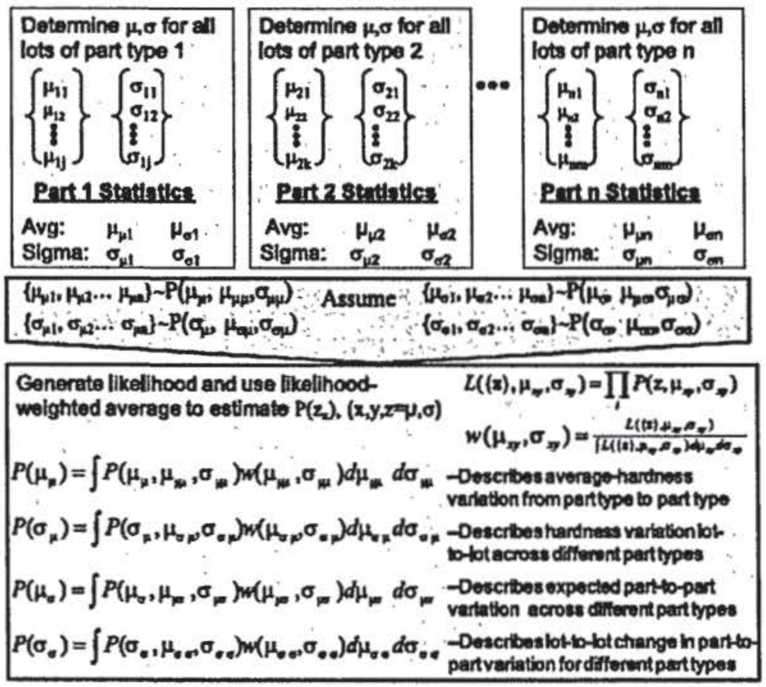

Fig. 4. A) Fitting the mean failure dose and standard deviation (μ_{ij}, σ_{ij}) for each lot j of each part type i to lognormal distributions yields 4 parameters for each part-type ($\mu_{\mu i}, \sigma_{\mu i}, \mu_{\sigma i}, \sigma_{\sigma i}$).
B) Fitting these parameters across part types to suitable distributions yields 4 distributions that describe process variability in terms of 8 parameters ($\mu_{\mu\mu}, \sigma_{\mu\mu}, \mu_{\sigma\mu}, \sigma_{\sigma\mu}, \mu_{\mu\sigma}, \sigma_{\mu\sigma}, \mu_{\sigma\sigma}, \sigma_{\sigma\sigma}$).
C) Because our dataset is small, rather than taking the single parametric combination that maximizes likelihood, we perform a weighted average over all parametric combinations using likelihood weights:

$$w(\mu_{xy}, \sigma_{xy}) = \frac{L(\{z\}, \mu_{xy}, \sigma_{xy})}{\int L(\{z\}, \mu_{xy}, \sigma_{xy})\, d\mu_{xy}\, d\sigma_{xy}}$$

The resulting distributions describe part-to-part, lot-to-lot variation over the range of similar part types in the process.

Looking at the data in Table III, the OP400 appears to exhibit greater variability—especially in its part-to-part standard deviation—from one lot to the next. As for the RH27, we initially perform the procedure outlined above excluding the OP400 data. Fig. 5 summarizes the various contributions to variability within the process. These curves indicate that while the OP400 is unremarkable in terms of its mean hardness, variation of mean hardness or expected part-to-part variation, part-to-part variation fluctuation is at the 90% WC level for the process—indicating that the part could be out of family for the process. Certainly, inclusion of the OP400 results in much broader distributions except for that of mean hardness.

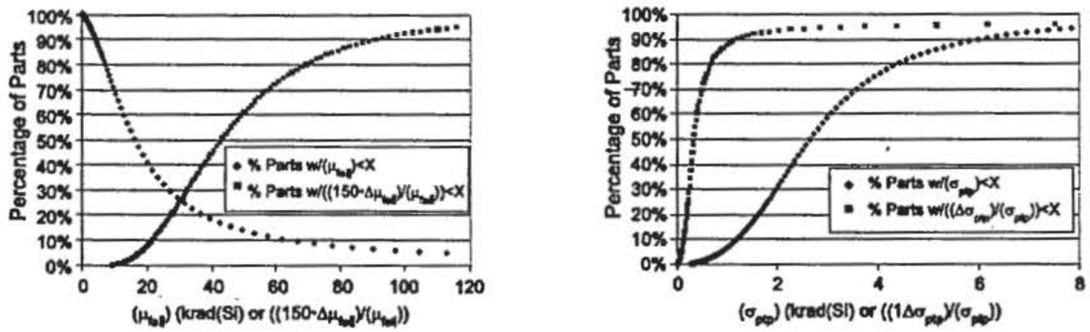

Fig. 5 Variability across Analog Devices' bipolar (>2.5 μm) OP series op amps is summarized by four distributions: 1) the variation of mean hardness over part-types ((μfail))—blue diamonds in a), 2) the variation of mean hardness from lot to lot (plotted as ($\Delta\mu_{fail}$)/ (μ_{fail}) magenta squares in a)—and scaled upward by a factor of 150 to plot it on the same scale as the mean), 3) the expected part to part standard deviation (σ_{ptp}) (blue diamonds in b) and 4)how the part-to-part standard deviation varies from lot-to-lot (plotted as ($\Delta\sigma_{ptp}$)/ (σ_{ptp}) in the magenta squares in b).

Conclusions and Recommendations

We have examined how to use statistical analysis of parts fabricated in a process to bound likely radiation behavior of other parts in the process for which we do not yet have data.

Our research has revealed that even with small, imperfect data sets drawn from public sources, we can place meaningful bounds and draw useful conclusions about likely performance of flight parts. If we have at least three lots of data for three different part types in a process, we can begin to disentangle the various contributions to variability for the process—part-to-part and lot-to-lot variation, as well as how susceptibilities to these variations change from one part type to another in the process. However, even if we lack data for multiple lots, we can still draw useful conclusions about how an "average lot" will perform—especially for radiation hardened part families like the LTC RH series of op amps. Indeed, if the process is sufficiently hard, even suspension data like that for the ADI XFCB process in table IV can place useful constraints on possible failure distributions.

Although the method outlined here is sufficiently robust to yield useful results even with small, imperfect datasets, its utility will improve with increasing dataset size or quality. In particular, if data are drawn from a long time series of lot qualification efforts with consistent test procedures and conditions, much greater precision is possible. Moreover, while here we have concentrated on a single parameter (Ibias), one can apply it across the board to all parameters or to different definitions of failure (e.g. functional).

In addition to use in qualification, the method should also find application in quality assurance—e.g. identification of process changes and other "out of family" behavior. Finally, because the method allows the various contributions to variability in a process to be estimated separately, its results can serve as useful input for physics-based modeling and process and circuit hardening efforts.

Acknowledgements

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References

[1] A. Namenson, "Lot uniformity and small sample sizes in hardness assurance," IEEE Trans. Nucl. Sci., vol. 35, no. 6, pp. 1506–1511, Dec. 1988.

[2] "Ionizing dose and neutron hardness assurance guidelines for microcircuits and semiconductor devices", MIL-HDBK-814, 2009.

[3] R. L. Pease, "Microelectronic Piece Part Radiation Hardness Assurance for Space Systems, Atlanta, GA, July, 19. 2004 NSREC Short Course.

[4] R. Ladbury, R. and J. L. Gorelick, "Statistical methods for large flight lots and ultra-high reliability applications," IEEE Trans. Nucl. Sci., Vol. 52, No. 6,pp. 2630 – 2637, Dec. 2005.

[5] R. Ladbury et al., "Statistical Model Selection for TID Hardness Assurance," IEEE Trans. Nucl Sci., vol. 56, no.6, pp. 3354-3360. Dec. 2009.

[6] Radhome Searchable database, http://radhome.gsfc.nasa.gov/radhome/RadDataBase/RadDataBase.html, 12/28/2009.

[7] Linear Technology Corp, ELDRS data: http://cds.linear.com/docs/Information%20Card/LTC%20Space%20Portfolio.pdf, 11/23/2009.

[8] Rob Davies, Personal Communication.

[9] S. Burns, Personal Communication.

[10] K. P. Burnham and D. R. Anderson, Model Selection and Multimodel Inference: A Practical Information-Theoretical Approach, 2nd ed., New York: Springer-Verlag, 2002.