

Method for Bounding Destructive Single-Event Effect Rates with Limited Statistics

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Destructive Single-Event Effects (SEE) Challenges

- NASA
- Destructive nature of single-event latchup (SEL), single-event burnout (SEB), single-event gate rupture (SEGR), etc. complicates testing and radiation hardness assurance (RHA)
 - Consequences for mission can be severe
 - In testing, every data point may represent a failed device \rightarrow limited statistics
 - Both factors necessitate conservatism in rate estimation, but how conservative?
- May have to combine data for several devices to improve statistics
 - Testing may be done at different facilities—different linear energy transfers (LETs)
 - If parts are thinned, variations may also result in different LETs for each part
 - Part-to-part variation combines with Poisson fluctuation
 - Effective LET may not apply
- 2007 method estimated SEE rates for a given confidence limit (CL) for poor statistics assuming Weibull σ vs. LET and Poisson fluctuations
 - For truly destructive SEE, # of events per run always equal to 1
 - Fluence to failure exponentially distributed about mean
 - Can we adapt the 2007 method?

Statistics of Destructive Failure

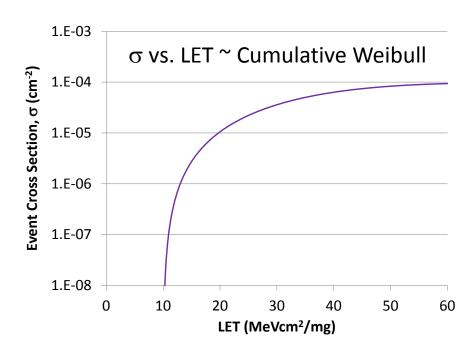


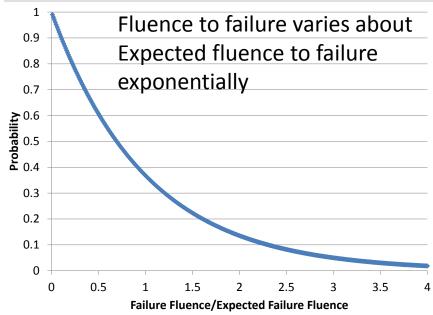
- Destructive SEE are Poisson processes
- # events=1, so σ =1/(Expected Fluence)
- Introduce model for σ vs. LET $\sigma(LET) = \sigma_0 \times \text{Weibull}(LET LET_0, w, s)$
 - σ_0 =Saturated cross section, LET_0 = onset LET; w, s = Weibull width, shape

 Fluence to failure varies about expected value (mean) according to an exponential distribution

$$P(F, \sigma(LET)) = \sigma(LET) \times \exp(-\sigma(LET) \times F)$$

Ignores part-to-part variation, but we could also introduce this factor





Solve Using Generalized Linear Model

- Likelihood over n data points, $L = \prod_{i=1}^{n} P_i(data_i : model)$
- Likelihood of fluences to failure for all runs, i=1 to n

$$L(\lbrace F_i, LET_i \rbrace, \sigma_o, LET_0, w, s) = \prod_{i=1}^n \sigma(LET_i) \times \exp[-\sigma(LET_i) \times F_i]$$

- σ_0 , LET_0 , w and s that maximize L give best fit to data $\{\sigma_{OBF}$, LET_{OBF} , w_{BF} , s_{BF}
- Confidence contour for confidence level CL given in terms of INV χ^2 distribution with degrees of freedom = # parameters in fit

$$L_{CL}/L_{BF} = \exp(-\text{INV}\chi^2(1-CL, \text{\#parameters} = 4))$$

- WC fit for confidence level CL is parametric combination yielding highest rate within parametric contour CL
- Can use Figure of Merit to find promising parametric combinations

$$- FOM = \frac{C * \sigma_{sat}}{LET_{0.25}^2},$$

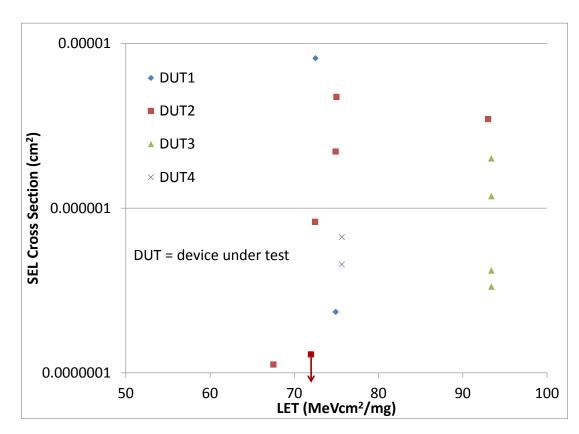
C depends on environment (~400 in geostationary orbit (GEO))

Fitting Poor Quality Data



SELs for TI SN54LVTH16244

<u> </u>		
DUT#	Eff. LET (MeVcm²/mg)	Cross-section (cm ²)
2	67.5	1.12E-07
2	72.5	8.26E-07
1	72.5	8.13E-06
1	74.9	2.34E-07
2	74.9	2.21E-06
2	75.0	4.74E-06
4	75.6	6.67E-07
4	75.6	4.55E-07
2	93.0	3.47E-06
3	93.4	3.33E-07
3	93.4	1.18E-06
3	93.4	2.00E-06
3	93.4	4.17E-07
2	72.5	Null

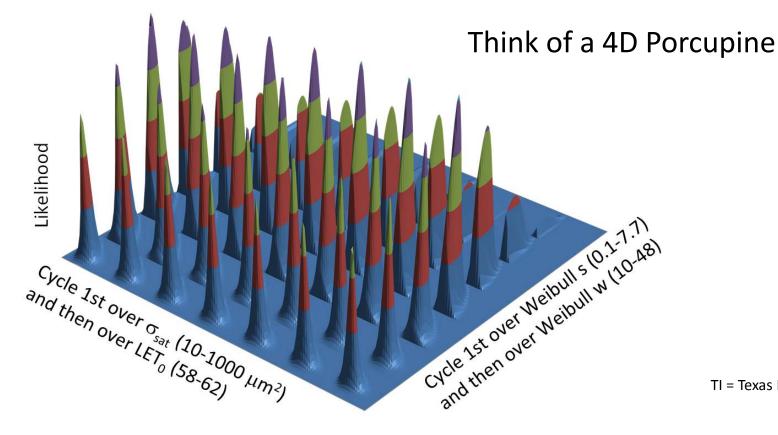


Only fourteen events with which to estimate a rate!

Probability in 4 dimensions?



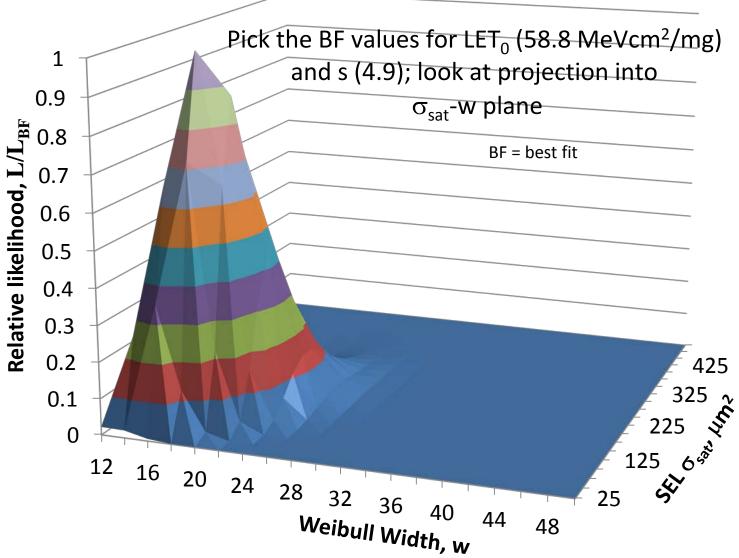
Likelihood of TI LVTH16244 SEL data for parametric combinations $\{\sigma_{sat}, LET_0, w, s\}$



TI = Texas Instruments

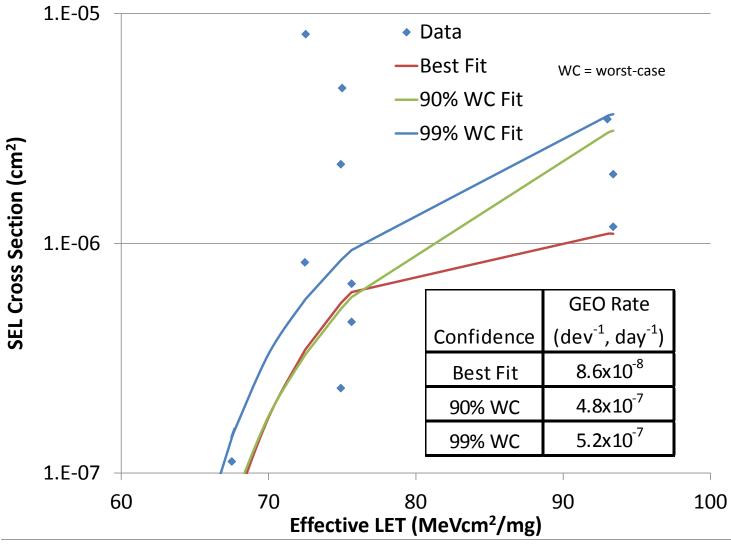
Projection into 2 dimensions?





How bad can it be?





Other Applications—Test Planning



- Experiment can be simulated prior to run to determine
 - Test conditions that best constrain/bound rate estimation
 - How to allocate scarce parts to best constrain/bound rate estimate.
 - How many parts near threshold?
 - How many to determine saturation?
 - How many in between?
 - Vary LET or accumulate statistics at the same LET?
- Can optimize allocation of parts and beam time in response to new data
 - Go to higher or lower LET to constrain fit?
 - Accumulate statistics or sample other LETs/test conditions?
 - Check for systematic errors, part-to-part variation by detecting failure fluences that deviation significantly from Poisson fluctuations (exponential about mean)
 - Are the data following effective LET?
 - And so on

Other Applications: Data Analysis



- Detection of outliers
 - Fluence to failure should follow exponential distribution about mean
 - Can data for different DUTs be combined, or do variations exceed Poisson errors?
 - Is lot-to-lot variation significant for a part type?
- Model comparison
 - Weibull form of σ vs. LET curve is only one candidate
 - Model can have angular, ion or any other dependence if sufficient data available to calibrate it—can be adapted to SEGR and SEB
 - Model can be output of a Monte Carlo or analytical
- Radiation Hardness Assurance
 - Comparison of SEE rates from different SEE analysts
 - Can determine level of conservatism by comparing estimates to worst-case results for different confidence levels
 - Allows comparison of SEE failure rates and electrical/mechanical failures estimated for similar confidence levels

Conclusions

- Destructive SEE represent serious challenges to hardness assurance
 - Consequences are severe, but statistics for bounding rates or always poor.
 - As a result, rates must be estimated conservatively,
 - but how conservatively?
- Generalized linear models offer flexible method to allow confidence level of rate to be determined
 - $-\sigma$ vs. LET can follow any model
 - Could be output of a physics-based Monte Carlo
 - Errors can be Poisson or more general (e.g. including part-to-part variation)
- Method can facilitate test planning
 - Allocation of parts, test LETs, etc.
- Also useful for data analysis
 - Detection of outliers, comparison of models, etc.
- Enables comparison of failure rates from other analysts or other causes