

Under-Constrained SEE Data: Implications for Estimating and Bounding SEE Rates

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Abstract—Increasingly scarce SEE testing resources and rapid growth of the New Space sector have increased the prevalence of under-constrained SEE data. We develop Monte Carlo tools to assess implications for SEE rate estimation. We also show that Bayesian Priors based on large datasets of SEL susceptible parts can augment under-constrained data and improve bounds on SEL rates. The resulting Bayesian Priors are also useful for bounding system SEL risk.

Index Terms—Single-event effects, reliability estimation, quality assurance; statistical techniques

I. INTRODUCTION

Criteria for good Single-Event effects (SEE) data have been discussed [1-8] at length. Refs. [1-4], [7] and [8] discuss the need for sufficiently high event counts to minimize the effects of Poisson errors on cross sections. Ref. [7] discusses how Poisson errors can affect estimation of Weibull fit parameters, and this work along with [5,6] discuss how such parametric errors can affect the accuracy of SEE rate prediction. Despite these detailed treatments, analysts still often confront poorly constrained SEE cross section (σ) vs. Linear Energy Transfer (LET) data. For SEE analysis, under-constrained does not simply mean that the number of data points is less than the number of parameters in the model. Because the cross section points have errors and because one is attempting to extract information about device response from the fit parameters, σ vs. LET is under constrained if the number of cross sections measured, where the data points fall on the curve, or errors (usually Poisson) on them significantly impair the analysis in which the data are used. Ref. [7] showed that 6 or more σ measurements could generate a good Weibull fit to the data as long as two points sampled the region near onset, two near saturation and two others on the rapidly rising portion of the curve. If any of these conditions are not met, determination of best values for Weibull parameters and their confidence levels is compromised. While rate estimation also suffers, the low cross sections near onset and low ion fluxes in the saturation region often attenuate errors on rate estimation, provided the rapidly rising portion of the curve is sampled accurately. Even with as few as 4 points, rates could often be estimated within a factor of 2-5x, although placement of the points on σ vs. LET is even more critical.

However, often the goal of SEE analysis is not to predict SEE rates, but rather to bound them, thereby ensuring hardware will meet requirements even for worst-case rates. Under-constrained data can pose significant issues for bounding SEE rates. Even assuming the cross section is a step function with a low onset LET (LET_0) may not bound the rate if all the test LETs are too low to measure the saturated cross section (σ_s).

Moreover, such a conservative approach may unnecessarily reject some parts, and it may not be viable in systems using large numbers of potentially susceptible parts with limited or no data. Methods for efficient use of under-constrained SEE data are highly desirable, because the incidence of such data is increasing for several reasons:

- 1) Insufficient time available for test
- 2) Overrunning allotted time due to the part SEE response being more complex than anticipated
- 3) Loss of beam time due to equipment failures
- 4) SEE test goals that did not include constraining fit to σ vs. LET curve for accurate rate estimation

The last factor occurs most often for SEE testing by “New-Space” ventures [9-10]. New Space offers the hope of capitalizing on the performance of state-of-the-art microelectronics, but at the same time, heavy reliance on many such parts often makes conventional SEE testing impractical in terms of both budget and schedule. Instead of conventional testing and hardness assurance, New Space testing often emphasizes to the extent possible recovery from SEE modes, with testing emphasizing susceptibility to destructive SEE (DSEE) at a few representative LET values, (similar to power device testing for Single-Event Burnout or Gate Rupture (SEB/SEGR)) [9]. Although such tests usually emphasize DSEE, they also yield cross section data for nondestructive SEE (NDSEE) modes, and while rate estimation for such a limited σ vs. LET curve is problematic, such data can give an idea of event frequency and the degree of mitigation required. The rapid growth of New Space, along with the increasing complexity of microelectronic parts and the increasing scarcity of beam time at heavy-ion accelerators suggest that even though using such data contradicts best practices, under-constrained SEE data will likely be increasingly common. The issues this poses may be exacerbated if New Space hardware is to be used for longer missions in more challenging environments.

In addition to the consequences of an SEE mode, the main information desired from under-constrained data is an estimated or bounding rate for the mode. Reference [7] showed that rate estimation can be relatively forgiving of poor data quality, while estimation of fit parameters for the σ vs. LET curve or bounding the rate to a particular confidence are not. Moreover, as the number of cross sections in the curve decreases, the fitting process becomes more sensitive to precisely where the points fall on σ vs. LET, as well as on systematic and statistical errors on the σ measurements. This can introduce significant subjectivity into the fitting process—especially when done “by eye,” making an automated, self-consistent, repeatable fitting approach even more important for under-constrained data.

Ref. [8] introduced such an automated likelihood-based fitting approach that finds not just the best-fit Weibull

parameters for σ vs. LET, but also those for the fit that bounds the SEE rate for any desired confidence level (CL). The approach was adapted in Monte Carlo (MC) studies to assess the effects of data quality on fit-parameter estimation [7]. Although MC studies have mostly been used in radiation effects for SEE rate estimation and hardening in complex parts [11-13], more relevant to this work, they have also been used in reliability studies [14-15], Design of Experiments (DOE) [5,6] and data quality studies [7]. These techniques are also well suited for assessing the potential impact of under-constrained SEE data on SEE rate estimation/bounding. Here we extend the preliminary work done in [7], applying MC methods to simulated under-constrained SEE data, assessing the potential impact of such data on rate estimation and bounding, developing guidelines for assessing such data if no better data are available and suggesting methods for improving results.

II. MONTE CARLO TOOL FOR UNDER-CONSTRAINED DATA

The Monte Carlo tool used for this analysis is similar to that used in [7], and employs the likelihood-based fitting routine introduced in [8]. This fitter capitalizes on the fact that observed SEE counts N_i^O for the i th LET will be distributed Poisson-wise about the expected/mean value $=\sigma(LET_i)F_i$. As such, the best-fit model for $\sigma_M(LET_i)$ will be that which yields predicted counts N_i^P that maximize the likelihood Λ :

$$\Lambda = \prod_{i=1}^n \text{Poisson}(N_i^O, N_i^P = \sigma_M(LET_i)F_i) \quad (1)$$

This fitting approach is called a Generalized Linear Model (GLM), which extends many of the advantages of linear regression to cases where variability is more complicated than linear regression allows [16]. We restrict ourselves to candidate models of 4-parameter Weibull because such a fit is required for most SEE rate estimation routines. This requires numerically finding the Weibull parameters that maximize Λ , but since the starting point and bin width of the search grid can be adjusted repeatedly for each parameter independently, the best-fit (BF) parameter values can be determined with arbitrary accuracy and the contours of the likelihood can be investigated over any range of the parameter space. This is important, because the near-normal behavior of Λ near its maximum allows approximation of confidence contours in the Weibull parameter space in terms of the ratio of the likelihood at the confidence limit CL (Λ_{CL}) to the maximum (Λ_{MAX}):

$$\ln\left(\frac{\Lambda_{CL}}{\Lambda_{MAX}}\right) = -0.5 * \chi^2_{INV}(CL, 4) \quad (2)$$

where the 4 represents the number of fit parameters. If one selects the parametric combination inside CL that maximizes the rate, this rate bounds the actual rate with confidence CL.

Use of the above fitting routine in a MC tool requires modifications because the fit must be performed on each of thousands of MC runs. Repeated rebinning and recentering for each run is not feasible, so the search is over parameter bins of finite width. However, the runs can be repeated until bin widths and position are optimized for the simulation as a whole. The number of bins for each parameter also must be limited to ensure the execution time is short enough to be useful. Compared to [7], the lower number of LET points allows the

number of bins to be expanded for Weibull shape s (from 6 to 9) and LET_0 (7 to 9). Also, unlike [7], the emphasis in this work is whether the fitter successfully finds estimated and bounding SEE rates. Distributions of fit parameters are mainly of interest to determine whether the fitter has found a real solution or merely bumped against the boundary of the search space (a risk for likelihoods based on few data points). We say the fit has failed if the 90% worst-case (WC) fit parameters favor $\sigma_s \geq 10x$ the generating limiting cross section σ'_s or if the 90% WC $LET_0 < 0.1$ of the generating value LET'_0 . Although the resulting errors on rates are often less dramatic than the errors on the parameters, large errors on the fit parameters result in rate errors—especially for bounding estimates. Fig. 1 illustrates the MC process schematically.

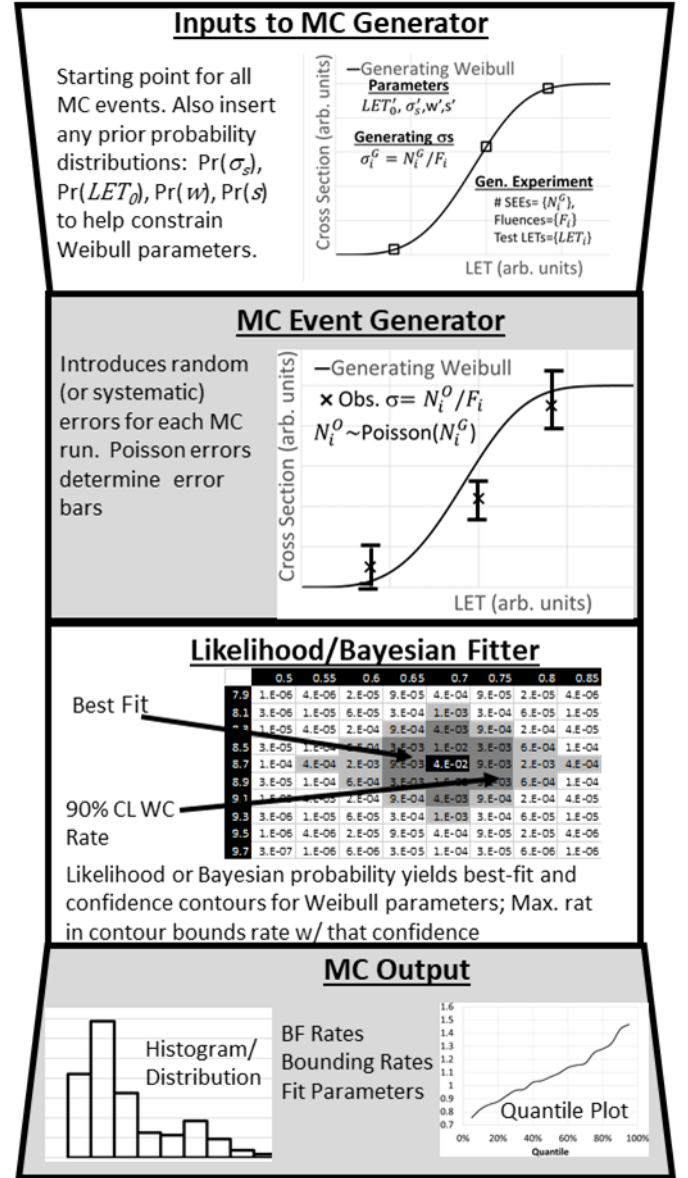


Fig. 1. The Monte Carlo technique facilitates investigation of how changes in an experiment affect the data produced along with subsequent analysis. Input includes generating σ vs. LET and details about the experiment (observed counts, test LETs, fluences, etc.). The MC generator introduces errors/variability into the study, while the fitter attempts to retrieve the original generating information. MC output compares the retrieved information to the generating scenario (plots, trend analyses, etc.)

As with the previous analysis, the current MC tool was implemented in Microsoft Excel™ and generates 1000 simulated SEE tests in ~1 minute with errors on cross section measurements determined by Poisson fluctuations about mean values. Although more complex fitting algorithms could be developed to also consider additional sources of error, random and systematic errors of the same order of magnitude would likely have comparable effects (e.g. 10% errors regardless of source ought to have similar impacts).

III. CHOOSING WHICH LETs—EXAMPLE SCENARIO

Selection of LETs for an SEE test has been discussed by several authors [3,5,7]. In general, it requires understanding the mission-environment ion LET spectrum, the ions on offer at the test accelerator, the technologies and construction of the Device Under Test (DUT) and the general form of σ vs. LET. When SEE data are under-constrained, some of these criteria are necessarily neglected. For instance, the tester may choose the ions to represent of portions of the mission environment LET spectrum (as for SEB/SEGR testing—solid curve in Fig. 2). Thus, $LET \sim 20$ MeVcm²/mg may be chosen to eliminate devices susceptible to proton-induced DSEE.[17] Devices may also be exposed to ions with $LET \sim 37$ MeVcm²/mg to identify those immune to DSEE for ions in or below the iron knee, and thus posing minimal threats for short missions in benign radiation environments. They may also be exposed to an ion (e.g., ~ 30 MeVcm²/mg) representing intermediate level of concern—where a susceptible device may be used if the effects of the SEE mode are mitigated. If susceptibility is worst case for ions incident normal to the die (as for SEB and SEGR in vertical power devices), these LETs may identify degrees of risk in the environment. However, if SEE σ depends on effective LET ($LET_{EFF} = LET/\cos(\theta)$, where θ is the angle to the normal), the flux of potentially significant ions decreases much more slowly than with LET (other curves in Fig. 2). Nonetheless, the LET values above are typical for many New Space vendors—often because they simultaneously test many different device types (including power devices) at ultra-high-energy ion accelerators (e.g. NASA Space Radiation Laboratory at Brookhaven National Laboratory [18]). As such, for purposes of illustration, we assume the under-constrained dataset has only 3 cross section measurements—(18-20, ~ 30 , ~ 37 MeVcm²/mg), as this suffices to expose challenges and to develop guidelines for using such data when better data are unavailable. We also look at two Weibull generating scenarios with similar parameters except for the shape s (see Table I). The reasons why the first LET is 18 MeVcm²/mg when $s=2$ and 20 MeVcm²/mg when $s=3.7$ will be discussed below.

IV. OPTIMUM DATASETS—AND WHY THEY ARE RARE

The success of under-constrained SEE data in bounding SEE rates depends on where the test ion LETs sample the curve as well as on the behavior of the curve itself. If the dataset contains σ measurements at only 3 LET values, the optimum dataset will have the central LET, $LET_c = LET_0 + w$. This is because when $LET = LET_0 + w$, the cross section will be $\sim 63\%$ of the saturated value, regardless of the value of s . Several trial-and-error analyses with the MC tool show that the lowest LET should sample the curve $< \sim 5\%$ of the saturated value and the

highest LET $> \sim 95\%$ of saturated. If the lowest and/or highest LET sample the curve nearer the middle, the dynamic range will be insufficient to discriminate between different possible curves, resulting in failure to find an adequate estimate or bound for the rate. (This is why the lowest LET for the generating scenario with $s=2$ was lowered from ~ 20 to ~ 18 MeVcm²/mg.)

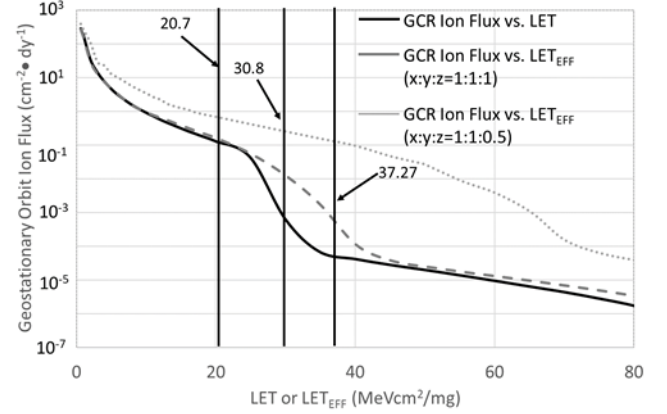


Fig. 2. Although ion flux vs. LET falls rapidly from 28 to 37 MeVcm²/mg (black curve), the fall is less rapid vs. effective LET (dashed and dotted curves).

TABLE I: σ vs. LET SCENARIOS FOR ANALYSIS

$LET_0 = 15$ MeVcm ² /mg, $\sigma_s = 5 \times 10^{-4}$ cm ² , $w = 15$					
$s=2$		$s=3.7$			
MeVcm ² /mg	σ (cm ²)	MeVcm ² /mg	σ (cm ²)	MeVcm ² /mg	σ (cm ²)
LET=18	0.00002	LET= 20.8	0.000015		
LET= 30.7	0.00033	LET=30.7	0.00035		
LET=37.6	0.00045	LET=37.6	0.00049		

When the 3-sample dataset is optimized as above, the fitter is efficient at returning the generating rate. Even as Poisson errors on cross sections increase due to decreased event counts (as low as 16 events), the errors on the best-fit SEE rate remain less than 50% for over 90% of MC events for both $s=2$ and $s=3.7$, although the relatively slower rise of cross section for $s=2$ results in slightly lower accuracy. (See Figs. 3a and 3b.)

Unfortunately, the real challenges for under-constrained data involve bounding the SEE rate to a required confidence. This is because with only 3 data points contributing to the likelihood, the analysis is susceptible to fluctuations in any of the points, and it becomes more difficult to exclude as improbable large regions in the fit-function parameter space. Fig. 4 shows the proportion of the time the fitter fails to find a 90% WC bound to the fit/rate because even unreasonable values for fit parameters cannot be excluded (as discussed in Section III). As SEE counts per σ estimate increase from 16 to 128, the rate of failure to find a bounding fit/rate decreases nearly linearly. This suggests that for LET values optimized to sample σ vs. LET and negligible ($\leq 10\%$) error bars on each σ estimate, a 3-sample dataset can estimate and perhaps bound SEE rates.

V. NON-OPTIMUM, UNDER-CONSTRAINED DATA

Unfortunately, not only will most under-constrained SEE data not be optimum, it may not even be clear how far the data stray from optimum. Fig. 5 shows that if the three LETs are

centered to the left (open, symbols) of $LET_0 + w$, the saturation region (and so σ_s) will be badly under-constrained, while test LETs centered to the right of the optimum (grey, dashed) will underconstrain LET_0 . Small changes can impact the ability to bound SEE rates. If Poisson errors are negligible (#SEE count=128 per σ) for σ vs. LET with $s=2$, and the the lowest LET to 20 from 18 MeVcm²/mg, the proportion of events for which the fitter fails to bound the rate rises from 7% to ~39%.

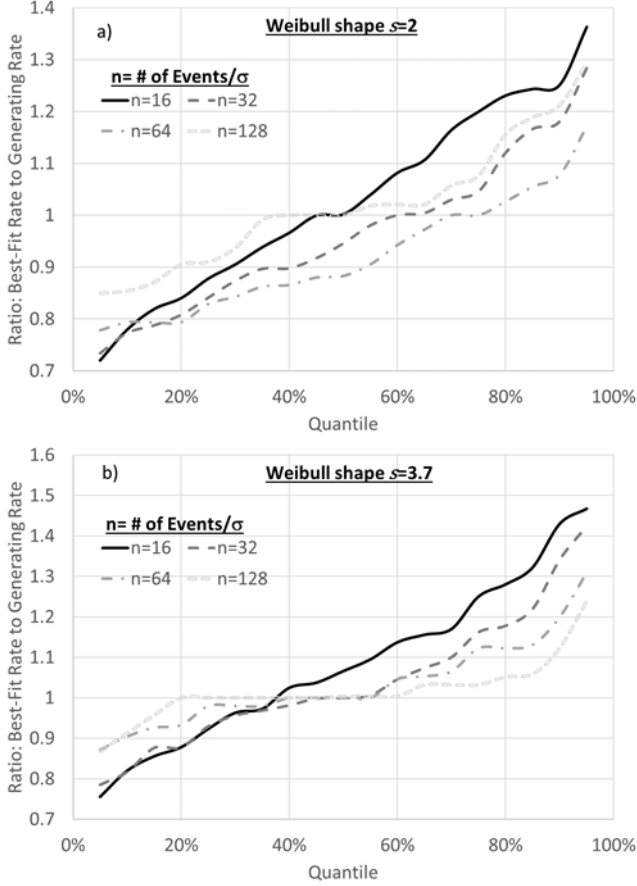


Fig. 3. If one is lucky enough that the 3-point sampling of σ vs. LET is optimized and centered on $LET_c = LET_0 + w$, one can often estimate the SEE rate within 50% of the correct value (that of the generating scenario).

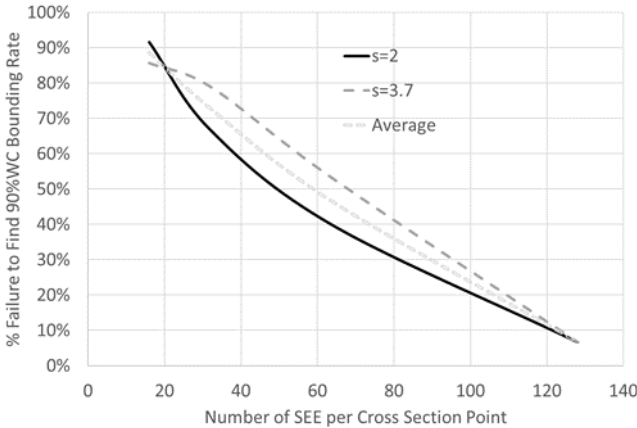


Fig. 4. Although optimized under-constrained SEE data can give a reasonable approximation of the SEE rate, it has a high probability of failing to bound the rate to a desired confidence, especially if Poisson errors on cross sections are large or σ vs. LET saturates slowly.

These discussions indicate the importance of understanding how much real data deviate from optimum condition and in which direction. One helpful strategy may be to capitalize on the Weibull-like behavior of σ vs. LET to better understand the data and potentially valid fits to it. Assuming Poisson errors on event counts are negligible so measured cross sections accurately estimate actual values, we observe that when $LET = LET_0 + w$, the argument of the Weibull equals 1, and the cross section will be at ~63% of σ_s , regardless of s . A 3-LET dataset can be broken into 2 LET intervals—lowest LET to central LET (LET_c) and LET_c to highest LET. If the increase in cross section over the left segment is $\Delta\sigma_L$, and that over the right segment is $\Delta\sigma_R$, we define the ratio $R_\sigma = \Delta\sigma_L / \Delta\sigma_R$. Here we consider only the case where the two LET intervals are equal and examine the behavior of R_σ when the dataset is optimal ($LET_c = LET_0 + w$), left of optimal and to the right of optimal. Because Weibull width acts as a scaling parameter along the LET axis, we express LET in units of w , and look at various values of s and displacements to the left or right (in units of w) of optimal. Fig. 6 summarizes the results graphically. When $R_\sigma < 1$, it is a clear indication that the LET triplet is displaced to the left of optimum and that $s > 1$. Beyond this limited result, tests involving R_σ are only effective if one knows $s > 2$ and ΔLET is sufficiently large ($0.2w - 0.3w$) to capture the curvature of σ vs. LET about $LET_0 + w$. When these conditions are met and $1.2 < R_\sigma < 1.86$, one can have high confidence that the LET_c is near optimal ($0.8w < LET_c < 1.3w$). Alternatively, given these constraints, $R_\sigma < 1.2$ indicates that the LET triplet is leftward of optimal, while $R_\sigma > 1.86$, indicates the triplet is to the right.

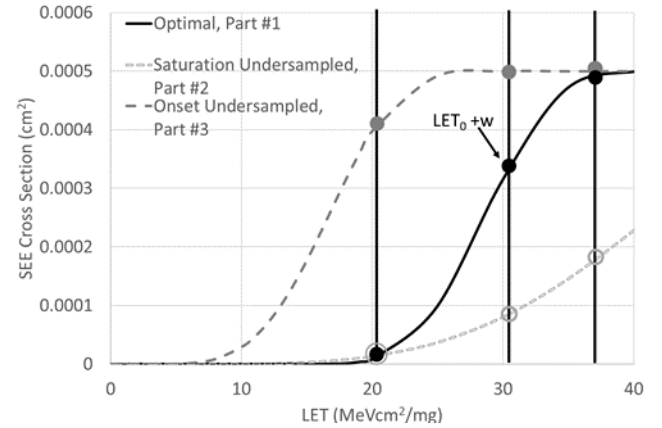


Fig. 5. If the LET triplet sampling σ vs. LET is far to the right of optimum, the onset region will be poorly determined, while if the triplet is to the left, saturation may not be well determined. Since often, many different parts may be tested together in a broad cross-section ion beam, one cannot optimize the LETs sampling σ vs. LET for all parts.

These observations indicate it will be difficult to assess the optimality of the dataset if the shape parameter $s < 2$. This is because for $s < 2$, the Weibull saturates slowly. While this limits the value of the test for slowly saturating σ vs. LET, relatively few datasets exhibit such behavior. Moreover, it may be possible to use data for similar parts exhibiting the same SEE mode to reduce the a priori probability for such fits. Similarly, the distribution of Weibull widths for the SEE mode for similar parts may also provide guidance for the range of LET needed to assess the data (based on the need for ΔLET to exceed $0.3w$)

noted above. Finally, if the cross section is slowly saturating ($s < 2$), it is usually appropriate to attempt to better determine σ_s , by adding data at high LET or using additional data to better constrain σ_s . Section VI illustrates the potential value of such data in the context of single-event latchup (SEL).

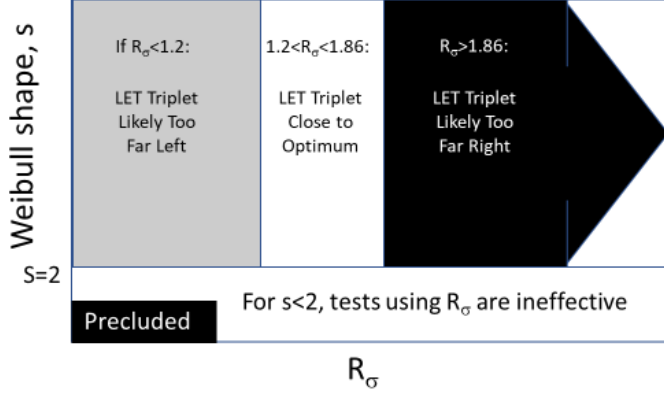


Fig. 6. If the Weibull shape parameter, $s > 2$, the ratio of cross section increase on the left segment of an LET triplet to that on the right, R_σ may indicate whether the triplet near optimum ($1.2 < R_\sigma < 1.86$), biased left of optimum ($R_\sigma < 1.2$) or to the right of optimum ($R_\sigma > 1.86$).

VI. PARTIAL BAYESIAN APPROACH

When SEE data fail to constrain the Weibull fit sufficiently to bound the SEE rate, it may be possible to further constrain the fit using general information other than the data at hand. The flow for this approach is nearly identical to that using the likelihood-based fitter, as Bayesian probability also requires the likelihood. However, for the Bayesian method, the likelihood for each parametric combination is multiplied by a Bayesian prior over the fit parameters of the model:

$$\Pr(\sigma_s, LET_0, w, s) = \Pr_\sigma(\sigma_s) \Pr_L(LET_0) \Pr_w(w) \Pr_s(s) \quad (3)$$

Priors can depend on any, all or none of the fit parameters. If we have no prior information to constrain one or more of the parameters, the prior for those parameters is constant over the range of interest (and 0 outside) and will not affect the analysis. If all the priors are flat, the analysis is identical to the likelihood method. We use a dataset of SEL susceptible parts assembled by colleagues at CERN to develop Bayesian priors that can constrain either σ_s or LET_0 for SEL susceptible parts.

Models predicting a priori SEL susceptibility of parts have proven unreliable. Past research has looked for correlations with vendor, fabrication process, feature size, fabrication line, and other factors, with no analysis predicting SEL susceptibility a priori [19–22]. Given the limited value of such similarity data, an alternate approach has been to assemble a large dataset of good-quality SEL data for a broad range of commercial CMOS parts [20–22]. One of the most comprehensive of these datasets has been compiled by researchers at the Conseil Européen pour la Recherche Nucléaire (CERN) from published data [14, 22–48]. By the kind permission of Andrea Coronetti and Ruben Garcia Alia, the full dataset is published here for the first time. Table II lists the parts in the database (82 parts with 35 functions from 20 vendors in several CMOS processes). Column 1 gives the part number; column 2, the manufacturer (mfg.); Column 3, the part functionality; Columns 4–7, the Weibull fit parameters

(with σ_s in cm^2 and LET_0 (labeled L_0 to conserve space) in MeVcm^2/mg) and the reference for the data in column 8.

Entries range from single-LET go/no-go SEL tests to data yielding 4-parameter Weibull fits. For this analysis, we had to ensure that the data had both LET_0 and σ_s well defined, so we returned to the source literature to verify this for each entry in the subset of the CERN dataset we used (51 parts, white background in Table II). We also omitted data for older SRAMs with extremely high SEL rates [25], since the goal was to develop a dataset representative of current susceptible parts.

When both LET_0 and σ_s are well defined, the power-law trend between these two variables emerges (see Fig. 7) when they are plotted on a log-log plot (yielding $R^2 > 0.43$ over 6 orders of magnitude variation in σ_s and 2 orders of magnitude in LET_0). Since a power law can be inverted, we can define either the distribution of LET_0 as a function of σ_s , or of σ_s as a function of LET_0 . These relations can be used as Bayesian prior probability distributions to improve constraints on the less-constrained variable (LET_0 or σ_s) in terms of the better constrained variable. This illustrates the potential importance of the techniques developed in Section V to determine whether the LET triplet is too far to the left or too far to the right.

The power-law relation between LET_0 and σ_s is empirical, and explaining it is beyond the scope of this work. Instead, we seek a simple model to describe both the trend and the variation around that trend. Because σ_s is easier to determine than LET_0 , we model LET_0 distribution given σ_s as a lognormal distribution with lognormal mean ($\mu_{\ln}$ equal to the log of the median LET_0 for that σ_s) given by the power law relation between LET_0 and σ_s , and constant lognormal standard deviation $s_{\ln}$.

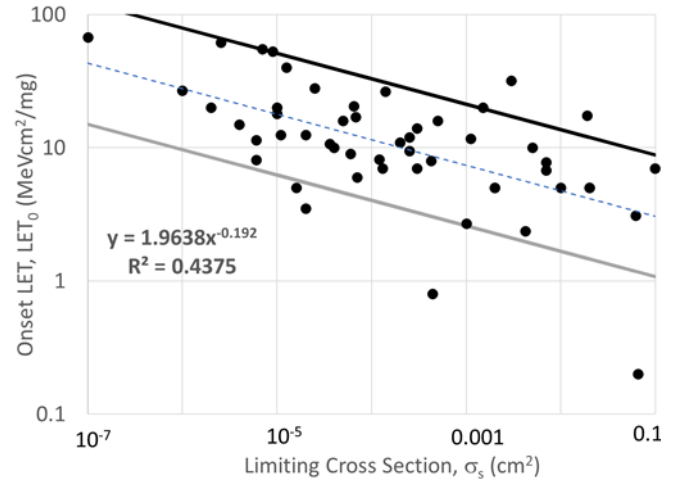


Fig. 7. Parts in the large CERN dataset of SEL susceptible parts exhibit an inverse correlation between LET_0 and σ_s , that persists over 2 orders of magnitude in LET_0 and 6 orders of magnitude in σ_s . A LN model with constant lognormal standard deviation and lognormal mean following the power law trend between LET_0 and σ_s , fits the data well (as indicated by the fact that nearly 90% of parts lie within the models 90% CL (black and grey lines).

Fig. 7 also shows the model's 90% confidence level (CL, lower in grey, upper solid black) as well as the power-law trend (dotted). The model fits the data well, with the 90% confidence interval containing very near 90% of the datapoints. To use this relationship as a Bayesian prior, one assigns each candidate fit based on its LET_0 and σ_s according to:

Table II: CERN SEL Database

Part #	Mfg.	Func.	σ_s	l_0	w	s	Ref.
3DCM681-1	3D Plus	Camera	2×10^{-4}	11	—	—	[31]
3DCM681-1	3D Plus	Camera	3×10^{-3}	32	—	—	[31]
54LVTH16244	TI	Logic	2.6×10^{-6}	62	—	—	[37]
74LVC373AD	TI	Logic	1.9×10^{-6}	15	—	—	[38]
74LVC3G17DC	TI	Logic	2×10^{-6}	20	26	3	[21]
93LC86BT	Microchip	EEPROM	2.5×10^{-4}	10	31	2	[43]
AD5328	ADI	DAC	4.4×10^{-4}	1	22	4	[45]
AD5370	ADI	DAC	4.2×10^{-3}	2	78	3	[26]
AD7609	ADI	Data Acquisition	2×10^{-5}	4	21	2	[43]
AD7714	ADI	ADC	1.4×10^{-4}	27	90	2	[43]
AD7801	ADI	DAC	4.3×10^{-4}	8	78	2	[29]
AD8629	ADI	Operational Amplifier	5×10^{-5}	16	—	—	[33]
AD9814	ADI	CCD sig. proc.	9.9×10^{-2}	7	—	—	[31]
ADS1271	TI	ADC	7×10^{-5}	6	—	—	[39]
ADS1271B	TI	ADC	3×10^{-4}	7	51	2	[25]
ADS1281	TI	ADC	1×10^{-7}	68	—	—	[34]
ADS7961	TI	ADC	4×10^{-6}	23	—	—	[40]
ADS8320	TI	ADC	6.8×10^{-5}	17	6	5	[47]
ADUM1100BRZ	ADI	Isolator	4×10^{-5}	10	25	4	[24]
ADV212	ADI	Video Codec	6.5×10^{-2}	0	16	2	[46]
ATMEGA1280	Microchip	Microcontroller	1×10^{-3}	3	—	—	[40]
CD74HC4067M	TI	Multiplexor	1.3×10^{-5}	40	15	5	[24]
DSPIC30F6014A	Microchip	Microcontroller	6.2×10^{-2}	3	23	2	[45]
DSPIC33FJ256GP7 10A	Microchip	Microcontroller	2×10^{-2}	5	—	—	[33]
ISL60002	Renesas	Voltage Regulator	4×10^{-6}	15	—	—	[32]
LTC1409	LTC	ADC	7×10^{-6}	55	36	3	[44]
LTC1595	LTC	ADC	1.2×10^{-4}	8	15	3	[43]
LTC1604	LTC	ADC	9×10^{-6}	53	32	2	[38]
LTC2271	LTC	ADC	2×10^{-5}	13	10	5	[42]
LTC2052	LTC	Operational Amplifier	1.3×10^{-4}	7	53	2	[43]
LTC2977	LTC	Power Manager	1×10^{-3}	3	—	—	[28]
LTC3708	LTC	Buck Regulator	6×10^{-6}	8	19	3	[42]
MAIA ROIC ASIC	TSMC	detector ROIC	6.5×10^{-5}	21	53	2	[48]
MAX2981	Maxim	Line Driver	1.1×10^{-5}	13	21	3	[43]
MAX2981	Maxim	Power Line Front End	1×10^{-5}	18	15	2	[43]
MAX2982	Maxim	XCVR	7×10^{-3}	7	18	3	[43]
MAX2982	Maxim	XCVR	1×10^{-2}	5	20	4	[43]
MAX6301ESA+	Maxim	Supply Supervisor	1.6×10^{-5}	5	20	1	[24]
MCP23018E/MJ	Microchip	Expander	2.5×10^{-4}	12	38	2	[24]
MCP6292E/MS	Microchip	Operational Amplifier	2.5×10^{-5}	28	38	4	[24]
MS1002A	Colibrys	Accelerometer	6×10^{-6}	11	—	—	[30]
MSP430F1611	TI	Microcontroller	8.6×10^{-3}	6	—	—	[33]
MSP430F1612	TI	Microcontroller	2×10^{-3}	5	—	—	[33]

Abbreviations used in Table II include:

ADC=Analog-to-Digital Converter

ADI=Analog Devices, Incorporated

ASIC=Application Specific Integrated Circuit

CCD=Charge-Coupled Device

Colibrys=Safran Colibrys

DAC=Digital-to-Analog Converter

DDR=Double Data Rate

DSP=Digital Signal Processor

Table II: CERN SEL Database (Continued)

Part #	Mfg.	Func.	σ_s	l_0	w	s	Ref.
PIC12F675-I/SN	Microchip	Microcontroller	1.3×10^{-3}	6	—	—	[38]
PIC18F452-I/PT	Microchip	Microcontroller	3×10^{-2}	6	—	—	[38]
PIC10F206-I /OTG	Microchip	Microcontroller	5.5×10^{-4}	6	—	—	[38]
PIC24J128GA010	Microchip	Microcontroller	2×10^{-2}	5	—	—	[33]
SF1600S	Colibrys	Accelerometer	7×10^{-3}	8	—	—	[30]
SIG60	Yamar	XCVR	1.1×10^{-3}	12	26	3	[43]
ST16C554DIQ64	MaxLinear	XCVR	3.2×10^{-3}	6	—	—	[33]
TLV5618	TI	ADC	6×10^{-5}	9	—	—	[34]
TMS320F28335	TI	Microcontroller	1.5×10^{-3}	20	—	—	[43]
TMS32F2805	TI	DSP	1.9×10^{-2}	18	26	5	[43]
TP551200RDC	TI	DDR Termination Regulator	3.6×10^{-5}	11	31	2	[47]
XC7K325T- 2FFG900C	Xilinx	FPGA	5×10^{-4}	16	—	—	[33]
XC7Z020-CLG484	Xilinx	FPGA	3×10^{-4}	14	20	1	[26]
10M08DAF	Altera	FPGA	2.5×10^{-6}	42	—	—	[33]
10M08SAE	Altera	FPGA	2.5×10^{-6}	42	—	—	[33]
A4980KLPTR-T	Allegro	Motor Driver	5×10^{-7}	40	—	—	[33]
AD7984BRMZ	ADI	ADC	2×10^{-2}	77	—	—	[33]
AD9117BCPZ	ADI	DAC	8×10^{-6}	42	—	—	[33]
AD9251BCPZ-65	ADI	ADC	3×10^{-6}	42	—	—	[33]
ADP2302	ADI	DC-DC regulator	3×10^{-6}	42	—	—	[33]
CY7C464A	Cypress	First-in-First-Out	1×10^{-2}	42	—	—	[33]
DAC5675	TI	DAC	5×10^{-7}	52	—	—	[33]
DG412	Vishay	Switch	1×10^{-6}	77	—	—	[33]
LM25066	TI	Power Manager	9×10^{-4}	87	—	—	[33]
LTC2337HMS	LTC	ADC	1.5×10^{-5}	77	—	—	[33]
LTC2449	LTC	ADC	1×10^{-3}	53	—	—	[33]
MAPS010163	Macom	Digital Step Phase Shifter	2×10^{-4}	41	—	—	[35]
MAX1156ETC+T	Maxim	ADC	1×10^{-4}	77	—	—	[33]
MS9001.D	Colibrys	MEMS	1×10^{-2}	53	—	—	[33]
Si4112-D-GT	Skyworks	Frequency Synthesizer	6×10^{-4}	16	—	—	[35]
Si6842	Skyworks	Isolator	5×10^{-5}	85	—	—	[33]
Si8233BB-C-IS1	Skyworks	Isolator Driver	2×10^{-5}	85	—	—	[33]
AS7C34098A- 10TCN	Alliance	SRAM	1.3×10^{-1}	0	28	7	[25]
BS62LV1600EIP55	Brilliance	SRAM	6×10^{-1}	2	14	2	[25]
CY7C1069AV33- 10ZXC	Cypress	SRAM	6.5×10^{-1}	3	32	2	[25]
IS61LV5128AI- 10TLI	ISSI	SRAM	2.4×10^{-1}	2	17	3	[25]
IS62WV20488BL- 25TLI	ISSI	SRAM	2.4×10^{-1}	4	23	4	[25]
K6R4016V1D- TC10	Samsung	SRAM	1×10^{-1}	0	35	7	[25]

Abbreviations (Continued):

EEPROM=Electrically Erasable Programmable Read Only Memory

FPGA=Field Programmable Gate Array

$l_0 = LET_0$

LTC = Linear Technology Corporation

ROIC= Read-Out Integrated Circuit

Sig. Proc.=Signal Processor

SRAM=Synchronous Random Access Memory

TI=Texas Instruments

TSMC=Taiwan Semiconductor

XCVR=Transceiver

$$P(LET_0|\sigma_s) = (LET_0 \times \sqrt{2\pi s_{LN}})^{-1} \times \exp(-((\ln(LET_0) - \mu_{ln}(\sigma_s))/s_{ln})^2) \quad (4)$$

where $\mu_{ln} = \ln(1.96\sigma^{-0.192})$, and $s_{LN}=0.82$. Priors for σ_s , w and s are flat over the range of interest and 0 outside. Rather than dealing with a likelihood for a given parametric combination, this method assigns posterior probability according to Bayes' Theorem:

$$P_{post}(\vec{W}, \{x\}) = \frac{\text{Prior}(\vec{W}) \times \Lambda(\vec{W}, \{x\})}{\int \text{Prior}(\vec{W}) \times \Lambda(\vec{W}, \{x\}) d\vec{W}} \quad (5)$$

where $\vec{W}$ is the vector of parameters corresponding to the Weibull under consideration $\{x\}$ is the data and $\Lambda(\vec{W}, \{x\})$ is the likelihood of the Weibull under consideration given the data $\{x\}$. The denominator on the right side of (5) is a normalizing factor ensuring the sum of all posterior probabilities is 1, but it can also be viewed as the probability of the data integrated over all possible Weibulls. The Prior places a limited constraint on the fits to the data. However, it places that constraint on the region of the curve that is least constrained by the data and depends on the portion that is best constrained. As such, it can improve estimates of best-fit, and, especially, bounding rates.

The use of likelihood in Bayesian methods to update the Prior probability distribution based the data presents an opportunity to compare the Bayesian approach to a pure likelihood-based fitter. For this study, all MC events were generated with $\sigma_s=5 \times 10^{-4} \text{ cm}^2$, $w=15$ and $s=2$ to minimize the effect of changes in cross section form. Different MC runs used different onset LET, moving the entire cross section with respect to the test LETs. One run (scenario 2) also moved the test LETs to increase under sampling near onset. This yielded 3 scenarios, each posing different challenges for achieving a good fit:

- 1) Minor skew right: $LET_0=9 \text{ MeVcm}^2/\text{mg}$ (median for Bayesian Prior given σ_s) with test ion LETs at 18, 30.7 and 37.6 MeVcm^2/mg
- 2) Significant skew right: $LET_0=9 \text{ MeVcm}^2/\text{mg}$, with test ion LETs at 25, 35 and 45 MeVcm^2/mg
- 3) LET_0 at at lower 90% CL: $LET_0=3.5 \text{ MeVcm}^2/\text{mg}$ (lower 90% CL Bayesian Prior bound, given σ_s), with test ion LETs at 18, 30.7 and 37.6 MeVcm^2/mg

The Bayesian approach selects the best fit as that having the highest posterior probability. To select the 90% WC fit, we sort the fits in order of decreasing probability and select the highest rate among the candidates with cumulative probability adding to 90%. This contrast with the Likelihood approach using eq. (2) to establish confidence contours.

Fig. 8 shows the 5th to 95th percentiles for the 3 scenarios above for the ratios of the best fit rate as found by the Bayesian and Likelihood methods to the Monte Carlo generating rate (that is 1 corresponds to the correct (generating-scenario) rate). The notation in the legend gives the fit approach used and the corresponding scenario—e.g. Bayes, #1 shows the result for the Bayesian fitter for Scenario #1. Fig. 9 repeats the analysis with the 90% WC Bayesian and Likelihood rates substituted for the best fit. While the Bayesian approach does not significantly affect the best-fit found, and has a small effect on the 90% WC bounding rate when the rightward skew is minor (Scenario 1,

with leftmost test LET to the left of LET_0+w), it significantly reduces the tendency to overpredict the 90%WC rate that occurs when all test LETs are to the right of LET_0+w . The improvement is most significant when the MC generating LET_0 is near the median of the Bayesian prior for the generating value of σ_s . However, even for scenario 3, where the generating LET_0 is near the lower bound of the 90% CL for the Prior, improvement ranges from a factor of 1.18 to 2.7 from the 5th to the 95th percentile. This is because the Prior reduces the probability most for the parametric combinations that yield unreasonably high rates for under-constrained data.

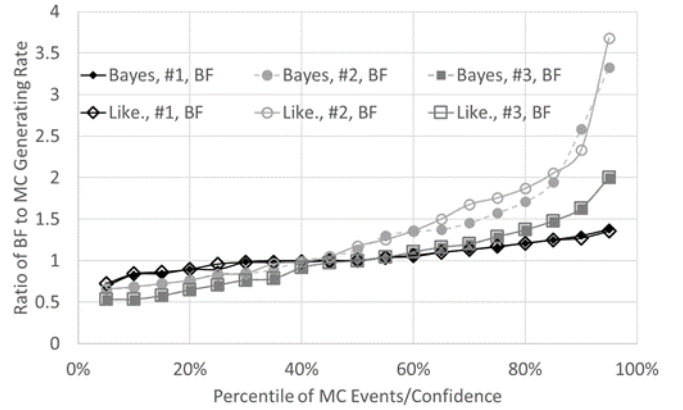


Fig. 8 A fitter using a Bayesian Prior over LET_0 tends to select (solid symbols) similar best-fit rates compared to likelihood alone estimation, regardless of whether rightward skew is minor (black), significant (light grey), and whether the generating LET_0 is near the median or near the lower 90% CL of the Prior.

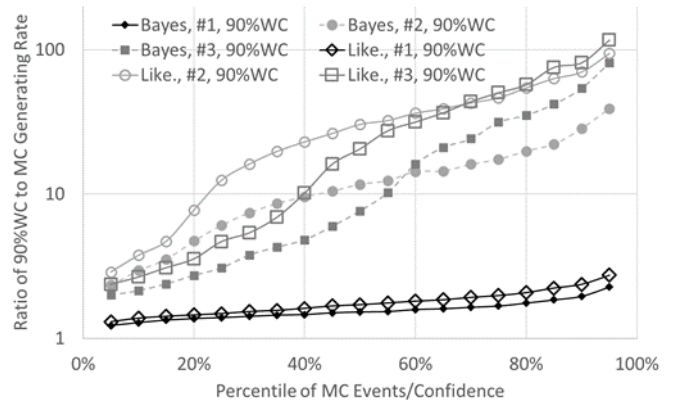


Fig. 9 Same as Fig. 8, but with the Best-fit rate replaced by the 90% WC. In all of the test cases, the Bayesian fitter outperforms the Likelihood-based fitter, because it eliminates unreasonable fits to the data triplet.

VII. PRIOR ONLY: SYSTEM-LEVEL APPLICATIONS

Attempting to assess the risk of potentially SEL susceptible parts used in a putative system before any SEE data are gathered may be the ultimate problem in under-constrained data. Moreover, the inverse correlation between LET_0 and σ_s suggests that a few percent of potentially susceptible parts latch up at rates high enough to pose significant risk to system reliability. Knowing that the risk is potentially significant, the question then becomes whether we can use the model introduced in section VI to bound the system-level SEL risk a priori to guide decisions for test planning and design.

Unfortunately, while the model constrains the low- or high-LET ends of σ vs. LET, it does not constrain the behavior in between, which depends on w and s . There are two approaches

we can take. Figure of Merit (FOM) rate estimation has only two parameters— σ_s and the LET where the cross section reaches 25% of σ_s —in addition to a constant factor C_E :

$$R_{FOM} = C_E \times \sigma_s / (LET_0 + w(0.288)^{1/s})^2 < C_E \sigma_s / LET_0^2 \quad (6)$$

The simplicity of the equation means that it requires less data to constrain those two parameters. Setting $w=0$ defines an upper bound on R_{FOM} that involves only σ_s and LET_0 . Using the CERN SEL dataset, we randomly select a value for LET_0 and then use the model from Section VI to bound σ_s at a randomly selected confidence level, defining an upper bound for the component's SEL rate. The model randomly selects LET_0 from the reduced 51-part dataset, taking into account that ~50% of commercial CMOS parts are SEL susceptible, and ~50% of susceptible parts fail destructively due to SEL [33]. The system rate is the sum of the rates for susceptible parts. We then repeat the analysis 10000 times and sort the results from lowest to highest system rate. We select the 90% CL highest rate for the MC run. Fig. 10 shows how heavy-ion testing with ions up to $LET=LET_T$ reduces the system rate by detecting and eliminating susceptible parts.

Another approach uses the subset of the CERN dataset containing full 4-parameter Weibull fits for the SEL data. As with LET_0 , we can randomly select w and s values from this subset—assuming it is representative of SEL susceptible parts as a whole. However, examination of correlations between parameters in this subset reveals that not only are σ_s and LET_0 correlated, but w and s are as well (correlation coefficient=-0.42). Unfortunately, no simple relationship exists between these parameters, so instead of a parametric model relating w to s , we randomly choose w - s pairs from among the parts in the subset of data. This allows us to reflect the w - s correlation without assuming a model. Using the randomly selected values for LET_0 , and w - s and the bound with randomly selected confidence for σ_s , we calculate R_{FOM} for each susceptible part and repeat the analysis that led to Fig. 10, yielding Fig. 11.

The curves in Figs. 10 and 11 behave similarly. They indicate that increasing the maximum test LET reduces the system rate nearly exponentially up to about 35 MeVcm²/mg by detecting SEL susceptible parts, but much more slowly at higher LET. We note that because the method used here uses R_{FOM} , for which LET dependence is inverse square for all LET, the decrease at $LET_T \sim 35$ MeVcm²/mg is not due to the iron knee in the GCR flux vs. LET. Also, the decrease for $LET_T > 35$ MeVcm²/mg is especially slow for more complex systems (40 potentially susceptible parts), likely indicating a higher probability of multiple susceptible parts. This information can be useful for test planning and for optimizing design reliability.

VIII. CONCLUSION

Although working with under-constrained like that considered here is a fraught proposition, such datasets are becoming increasingly common as New Space continues to grow, beam time becomes scarcer, and devices become more complex and difficult to test. Developing techniques to extract as much information about likely SEE rates and to minimize the risks posed by using such data could significantly increase the amount of usable SEE data available. As noted here, if the

LETs are optimized and errors on cross sections are small, it is possible to bound the SEE rate with fair confidence. Unfortunately, such optimal data is unlikely to happen by chance or with a one-size-fits-all test approach. When test LETs are skewed significantly to the right or the left of optimal, the limited constraints imposed on σ vs. LET fail to eliminate fits that result in very high rates (often >100× the actual rate) with significant confidence. Such fits often fail to effectively constrain the fit parameter opposite the test-ion LET skew (e.g., LET_0 for rightward skew, σ_s for leftward). The techniques outlined in Section V (and especially Fig. 6) can provide guidance for determining whether the LET triplet is skewed right or left and for likely ranges for s and w . This is useful for selecting a few additional test LETs or for attempts to supplement the information in the σ vs. LET measurements with additional constraints—such as Bayesian priors like those developed in Section VI.

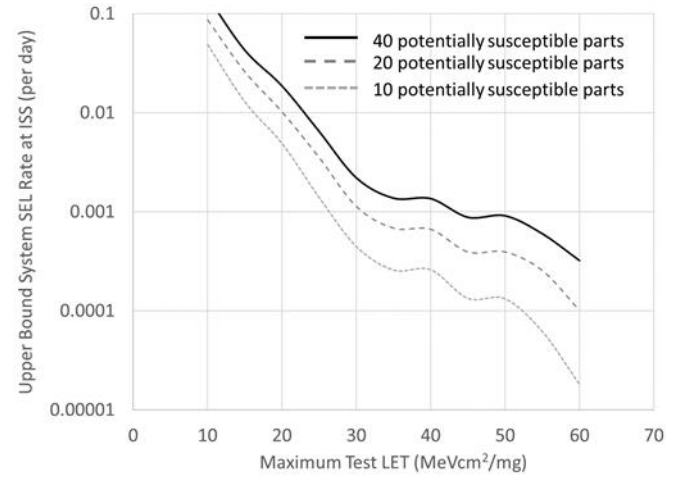


Fig. 10 With bounding part SEL rates assuming a step-function σ vs. LET curve (that is, $w=0$), system SEL rate drops ~exponentially with increasing maximum test LET up to about 37 MeVcm²/mg and significantly more slowly above this level. This reflects not just the falling Galactic Cosmic Ray flux vs. LET, but also the inverse correlation between LET_0 and σ_s . Above this level, the rate for complex systems (>20 potentially susceptible parts) improves especially slowly with increasing LET_T .

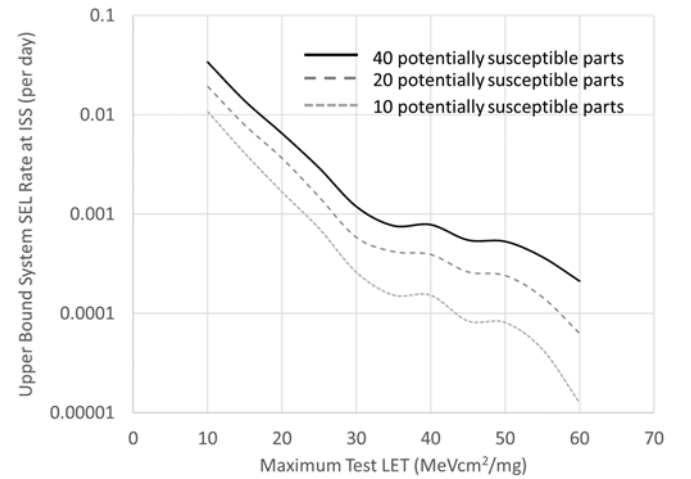


Fig. 11 If the Weibull width and shape parameters in the CERN dataset are representative of those for SEL susceptible parts generally, w - s pairs can be selected (to account for their correlation), allowing use of true FOM rates, rather than bounds used for Fig. 10. This reduces rates by about 5x for low test LETs and ~40% for high test LETs.

The models developed in Section VI are well suited for situations where data are sparse—whether a priori analyses to bound system-level risk or Bayesian fitting routines for bounding SEE rates. The power-law nature of the trend between LET_0 and σ_s means they can model the probability of either of these parameters in terms of the other. Usually, it is easier to model LET_0 in terms of σ_s , since determining or bounding σ_s requires only a single high-fluence run at LET sufficiently high that cross section is saturated (or nearly so). Determining LET_0 usually requires multiple high-fluence runs at LETs bounding LET_0 on either side. However, a null result at sufficiently high LET could be used to determine an upper bound on σ_s .

Monte Carlo techniques are well suited for understanding biases, limitations and potential utility for under-constrained data, as well as for assessing the effectiveness of remedies, such as the evaluation techniques to assess skew (Section V) and the Bayesian approaches of Sections VI and VII. To facilitate these analyses, we developed a compact fitter that could use either Likelihood methods or Bayesian probability. The Bayesian fitter could use a Prior constraining LET_0 as a function of σ_s or vice versa. This allowed direct comparison of the effectiveness of the remedies. We also applied the Bayesian priors to constrain system-level risks associated with use of potentially SEL susceptible parts even before test data are gathered for them, as long as the dataset upon which the Priors are based is representative of the parts used in the system. This work shows that although under-constrained data are plagued by uncertainties, they can constrain SEE rates—especially if they can be supplemented with additional data that addresses these uncertainties or if other pertinent constraints can be introduced, as for example was done with the Bayesian Priors. It is hoped that similar Bigger Data analyses can also yield useful correlations for other SEE related threats, since the prevalence of under-constrained data looks likely to persist.

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