

## Methodology for Correlating Historical Degradation Data to Radiation-Induced Degradation System Effects in Small Satellites

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This work is sponsored by NEPP Grant and Cooperative Agreement Number 80NSSC20K0424

08/07/2022



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QubeSat – tech demonstration mission of quantum gyroscopes in space University of California, Berkeley

- Important for an engineering team to have a general understanding of their system's failure probability
- Multiple rounds of radiation testing can be prohibitive due to test facilities' costs (costing >\$1k per hour)
- We propose a method for deriving a preliminary system-level failure probability from component failure data.
  - Device-level failure probabilities from historical device data
  - Generates system-level failure probability through a Monte Carlo process







Linear Voltage Regulator (LM317KCS) Texas Instruments

- **Objective**: Use Bayesian analysis to derive failure probabilities from radiation databases
- **Purpose**: Useful for small satellite applications with short development timeframes and significant utilization of COTS components
- **Case example**: A selected commercial BJT (2N2222) in a self-designed linear voltage regulator was found to have a high degradation probability

### Methodology

For Extracting System-Level Probability from Component-Level Degradation





### **Bayesian Analysis** For Estimation of Component-Level Probabilities

$$P(A \mid B) = \frac{P(B \mid A) * P(A)}{P(B)}$$

 $Posterior = \frac{Likelihood * Prior}{Normalization} \#$ 



### Kernel Density Estimation (KDE) For Component Probability Distribution Extraction

$$\hat{f}(x) = \sum_{observations} K\left(\frac{x - observation}{bandwidth}\right)$$

$$n^{\frac{-1}{(d+4)}}$$

$$p(\mathbf{x} \mid \boldsymbol{\mu}, \boldsymbol{\sigma}^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\mathbf{x}-\boldsymbol{\mu})^2}{2\sigma^2}} \#$$

$$p(\mathbf{x} \mid \boldsymbol{\mu}, \sigma^2) \propto e^{-\frac{(\mathbf{x}-\boldsymbol{\mu})^2}{2\sigma^2}} \#$$

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### Monte Carlo Method For System Probability Distribution Extraction

Inverse Cumulative Density Function (ICDF) 6 BJT's GDF based on LTspice's Random Number Generator (Input) 5 4 BJT's GDF 3 2 1 0.0 0.2 0.4 0.6 0.8 1.0 CDF



# Experimental Radiation Database 2N2222



- GDF = Gain Degradation Factor
  - Ratio of post-rad gain to pre-rad gain
- For 100 krad(SiO<sub>2</sub>), the distribution is approximately Gaussian
- For 300 krad(SiO<sub>2</sub>) and 1 Mrad(SiO<sub>2</sub>), appears more like a multi-modal distribution
- We approximated the 100 krad(SiO<sub>2</sub>) as a Gaussian

R. Ladbury and B. Triggs, "A Bayesian Approach for Total Ionizing Dose Hardness Assurance," IEEE Trans. Nucl. Sci., vol. 58, no. 6, pp. 3004–3010, Dec. 2011.

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### Simulation Setup

#### Using LTspice for Monte Carlo Simulation of System of Degradation

 ICDF
 ITSpice

 Component-level
 LTSpice

 System-level



Figure represents random sampling of the ICDF of components with TID degradation using the Monte Carlo feature in LTspice to produce a PDF of system behavior at the output

### **Simulation Results** Histogram of LTspice's Simulation Results

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**Distribution Obtained from KDE analysis of LTspice output histogram** 





### Conclusions

