Predictive Maintenance Strategies to Prevent Radiation Induced End-of-Life Failures

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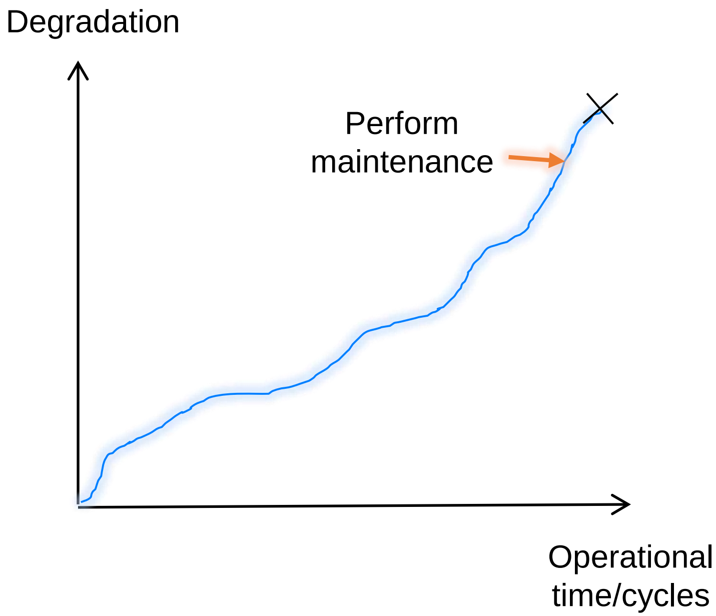
TE-EPC-CCE

Introduction

- Our designs are radiation tolerant up to certain levels
  - In some cases not sufficient for system lifetime
- → Replacement or Rotation strategies

Courtesy of M. Barros Marin

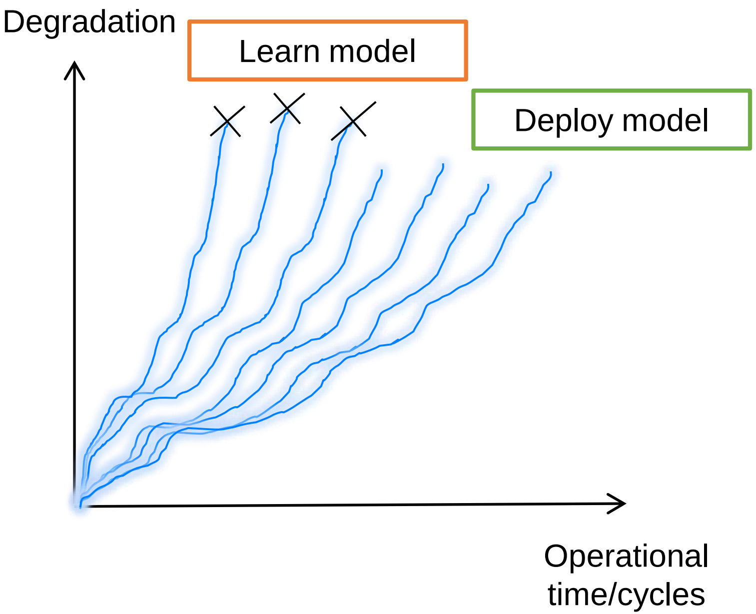
Introduction – Predictive Maintenance



Act timely before failure – Challenges:

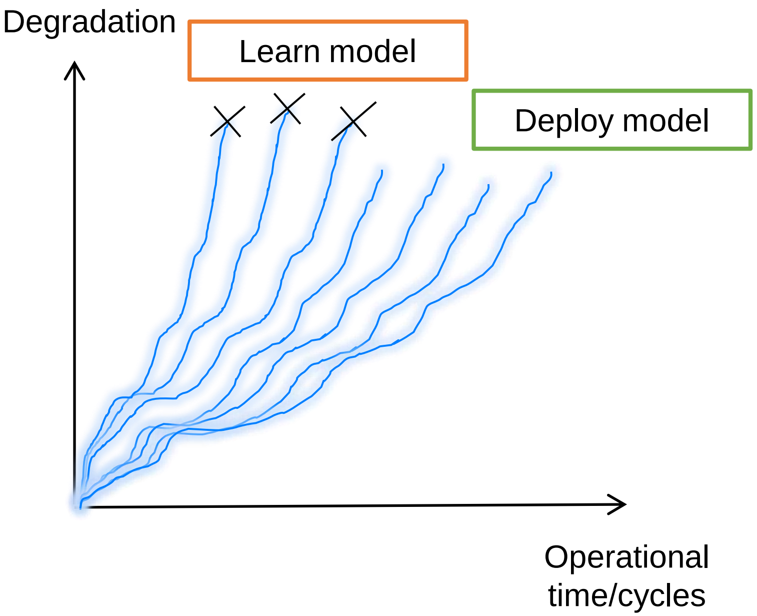
- Develop degradation models
- Data is expensive
  - Testing
  - Operational experience
  - Expert knowledge

Introduction – Predictive Maintenance "4.0"



- Sensing, collecting and storing data from connected devices is becoming cheaper
- IoT:
  - Connected devices
    - → more data
    - → more precise models
  - Deploy on all systems

Introduction – Predictive Maintenance “4.0”



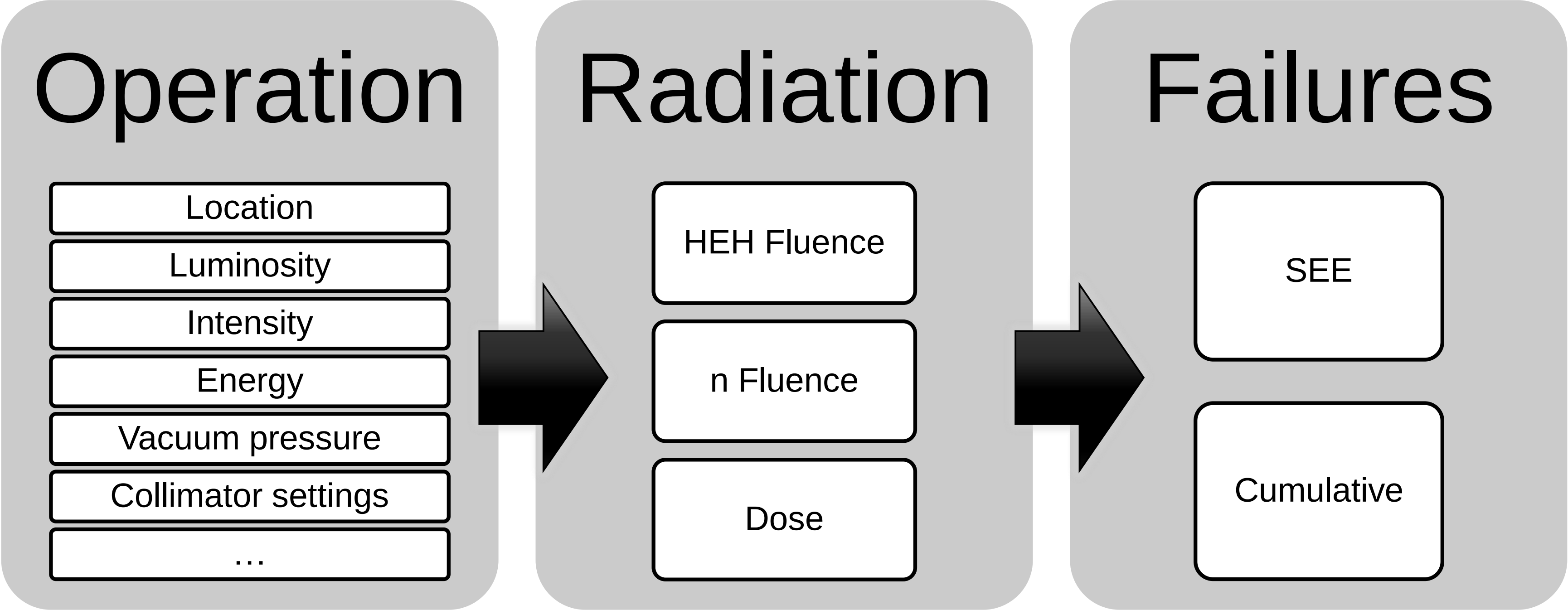
- Measure radiation (Collected and stored in a database)
  - → Sensing, Collecting, Storing ✓
- Large amount of devices
  - → Build accurate models ✓

Introduction – FGClite

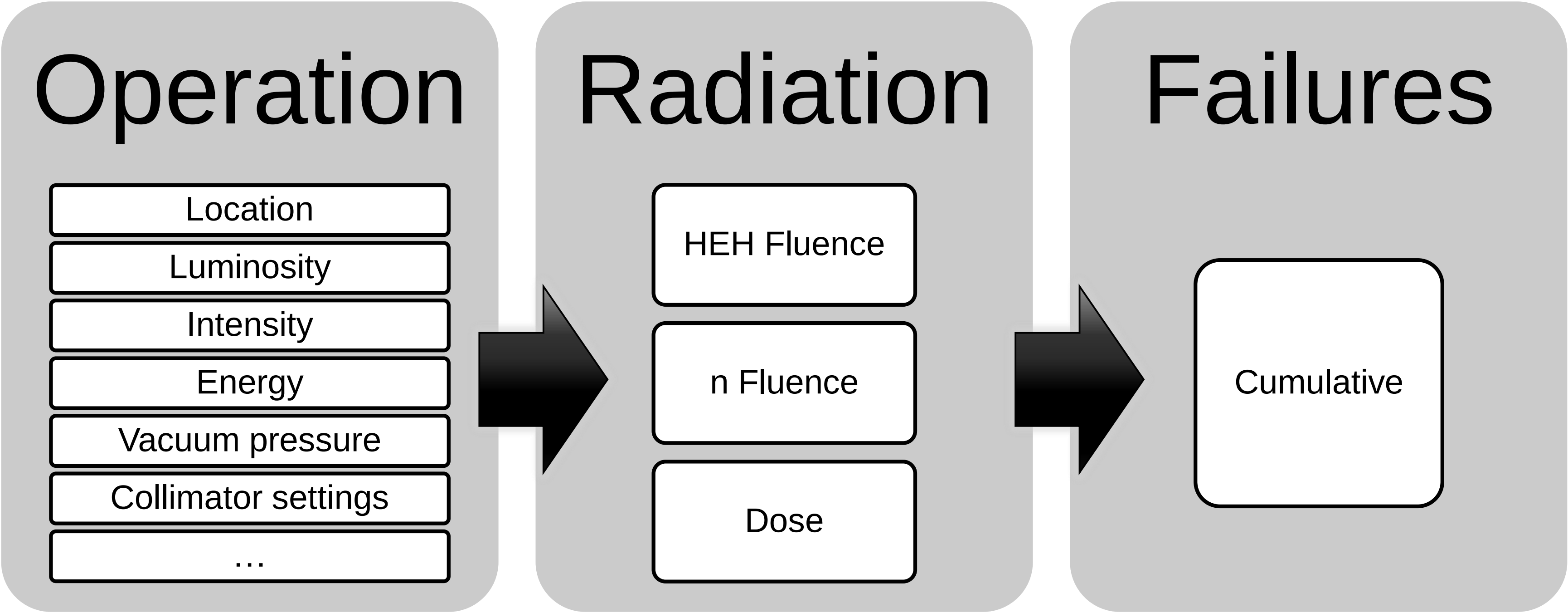
- Radiation tolerant controller for LHC power converters
- 754 devices installed
  - 300 more to be installed
  - Various locations

- Measure radiation (Collected and stored in a database)
  - → Sensing, Collecting, Storing ✔
- Large amount of devices
  - → Build accurate models ✔

Method – Radiation Effects

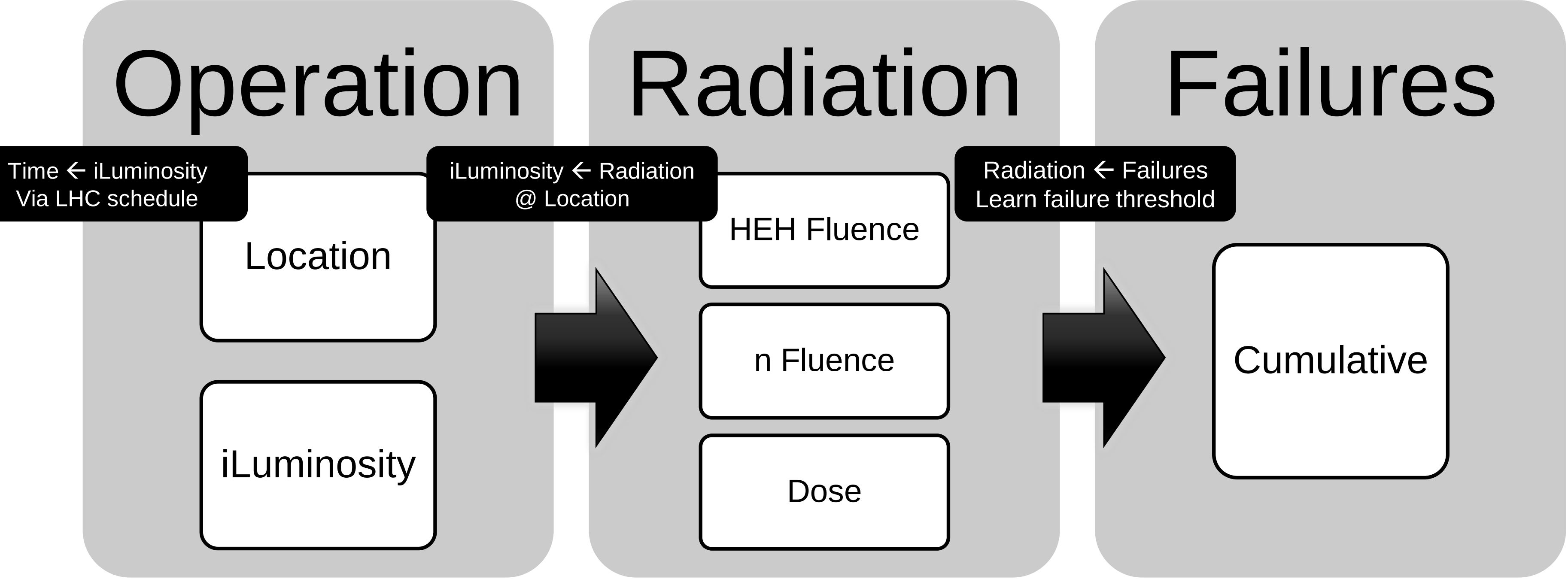


Method

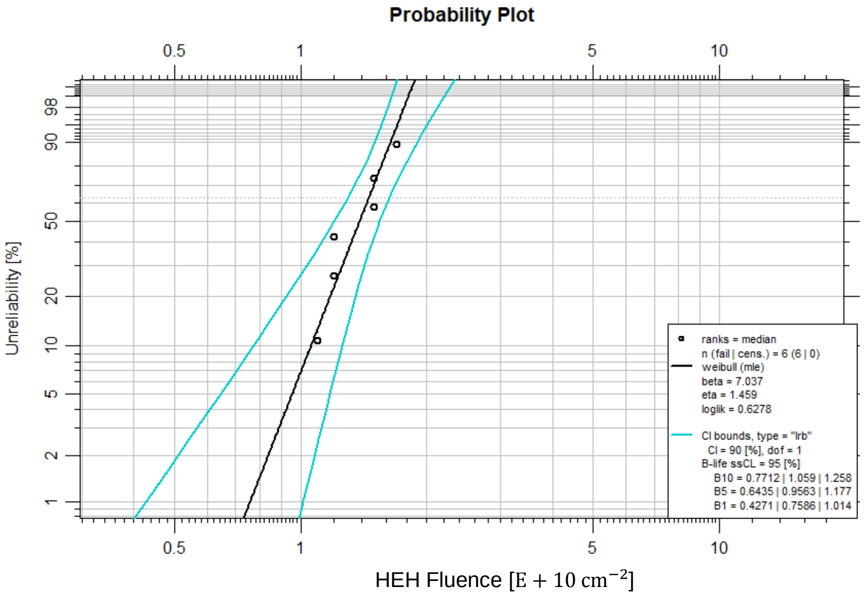

Operation
Location
Luminosity
Intensity
Energy
Vacuum pressure
Collimator settings
…
Radiation
HEH Fluence
n Fluence
Dose
Failures
Cumulative

Method

i = integrated

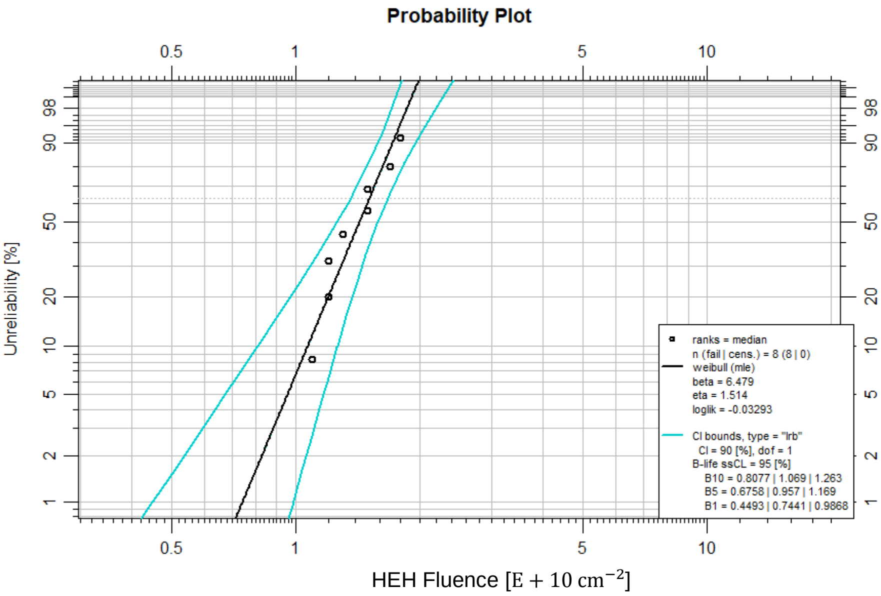


Method – Failures → Radiation



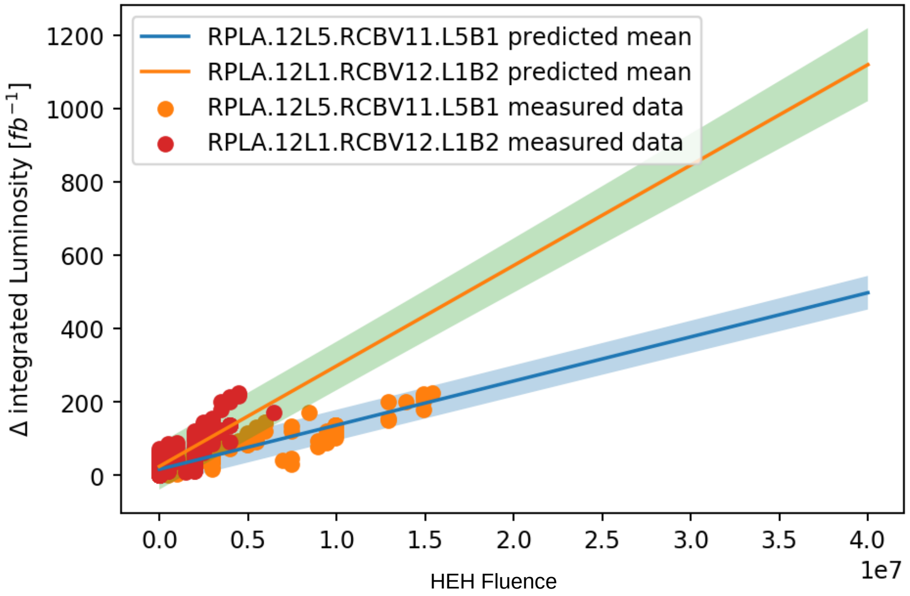
- Obtain failure threshold globally by Weibull-fit
  - Failure probabilities
  - Confidence levels

Method – Failures → Radiation



- Obtain failure threshold globally by Weibull-fit
  - Failure probabilities
  - Confidence levels
- Successively refine data-set
  - Data from Testing + Operation
    - Weighing possible

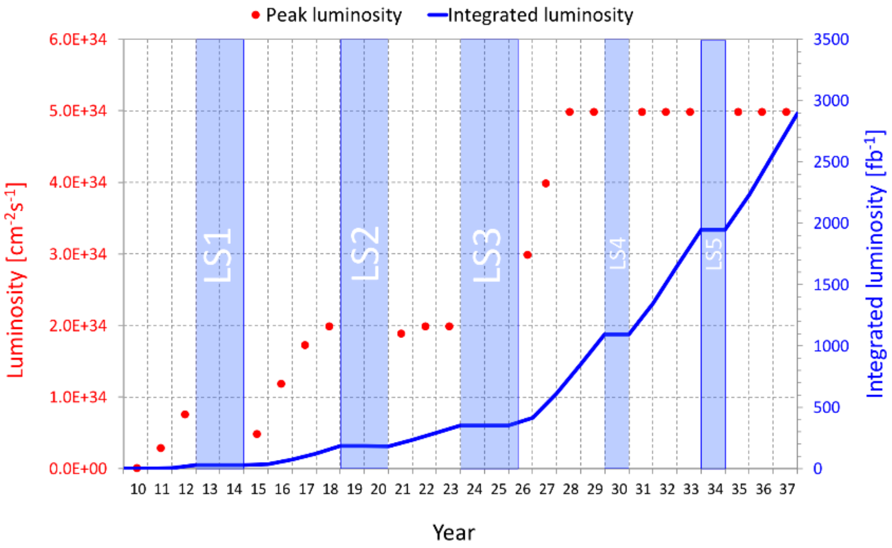
Method – Radiation @ Location → iLuminosity



- Obtain location specific model
- Using robust ML algorithms (Bayesian ridge regression)
  - Plus: confidence bounds
  - Re-train models automatically

Method – iLuminosity → Time

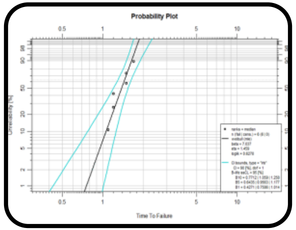
i = integrated

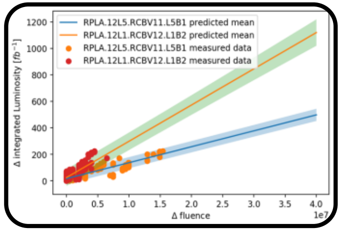


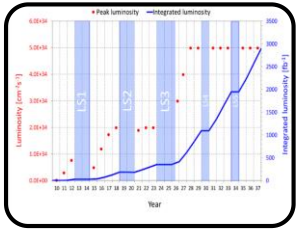
- Schedule maintenance for
  - Next TS
  - Next LS
  - …

Example – Failures → Radiation → iLuminosity for Optocoupler in FGClite

i = integrated







Operational failures (assumed):

5% failure probability

(@ 95% confidence):

0.64E+10 cm^{-2} HEH

(@ML: **0.96E+10 cm^{-2} HEH)**

Optocoupler @ RCBV11.L5B1:

Currently **5.5E+8 cm^{-2} HEH**

→RUL (@95% confidence):

1619 fb^{-1}

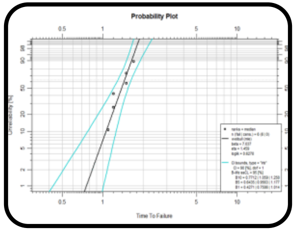
(@ML: **2670 fb^{-1})**

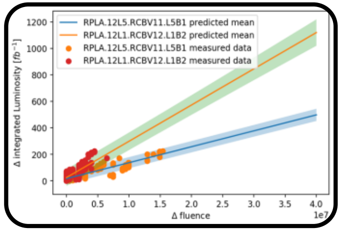
→ Exchange module in 2033

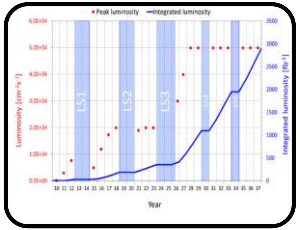
(before LS5)

Example – Failures → Radiation → iLuminosity for Optocoupler in FGClite

i = integrated







Operational failures (assumed):

5% failure probability

(@ 95% confidence):

0.64E+10 cm^{-2} HEH

(@ML: **0.96E+10 cm^{-2} HEH)**

Optocoupler @ RCBH14.R5B2:

Currently **2.5E+8 cm^{-2} HEH**

→RUL (@95% confidence):

3134 fb^{-1}

(@ML: **5075 fb^{-1})**

→ Survives until 2040

(after LS5)

Summary

- Simple and robust empirical method
  - Generally applicable
  - Sensing of radiation required
  - Also applicable if no prior radiation tests available
- End-to-end UQ
  - Wrong model assumptions are reflected by increased uncertainty
  - Can be used to test quality of models
- Challenges if deployed on larger scale:
  - Failure data acquisition
  - Persistence for device rotations

Thank you for your attention!

Method

- Goal: Build a model to forecast radiation wear-out
  - Based on data collected with FGClite