Advanced Estimation of Remaining Useful Lifetime for Power Modules

Kirill Ivanov, Horst Lewitschnig

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Importance of Reliability

- **Unplanned downtime** costs world's 500 biggest companies **11%** of their revenues [1].

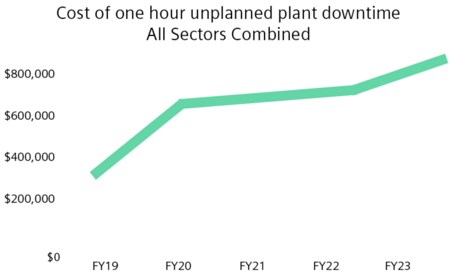

Figure 1: Source: Siemens | The True Cost of Downtime 2024 [1]

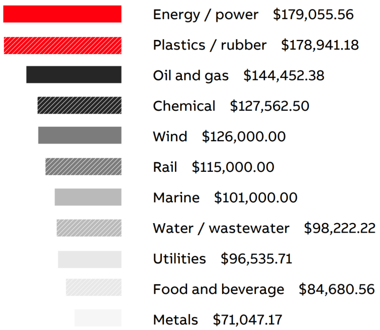

Figure 2: Source: Value of Reliability | ABB Survey Report 2023. [2]

Importance of Reliability

- **Unplanned downtime** costs the 500 biggest companies **11%** of their revenues [1].
- **IOT** has allowed companies to collect data on the **condition** of their machines.
- **Predictive Maintenance** with **Remaining Useful Lifetime** (RUL) prediction allows to avoid failures and over-maintenance.

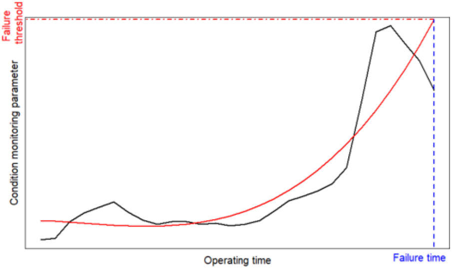

Figure 3: Typical RUL prediction approach.

Reliability in Microelectronics

- **Power modules** (PM) are widely used in inverters and power conversion equipment.
- Surveys [3] concluded that PMs (IGBT) were chosen by 31% of respondents as **fragile components**.
- Power module degradation is inherent and it is ongoing with operations.

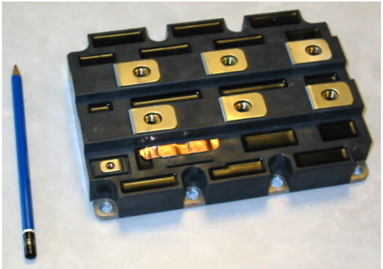

Figure 4: Power module [4].

Physics-Driven Degradation Modeling

Typical Degradation Mechanisms

- Die attachment delamination,
- Solder joint cracking,
- Bond wire fatigue.

Die attachment delamination - Physical Model:

- VDS increases due to impaired thermal resistance,
- Cubic polynomial matches known physics of fatigue crack propagation and captures degradation.

Two-Phase Behavior

- Early phase: High variance - measurement effects,
- Late phase: Low variance - dominant failure mechanism.

Problem statement

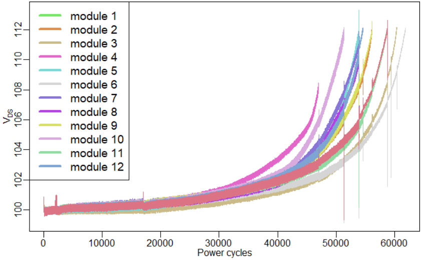

Figure 5: Power module degradation data.

- PMs show **linear drift** at early stages, followed by an **exponential degradation** pattern.
- Once **voltage drain source** (V_{DS}) is above a certain threshold, the module is considered to have reached its **end of life**.
- A scenario of **on-line** RUL prediction with **limited calculation resources** is considered.

Further patterns in stress test data

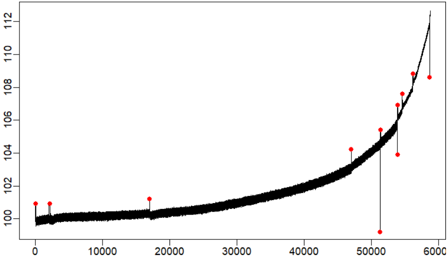

Figure 6: Measurement errors.

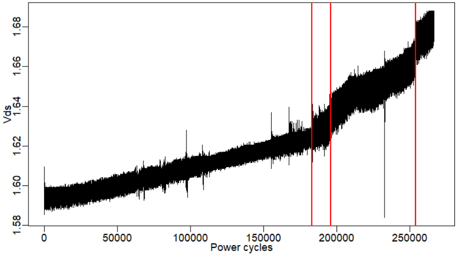

Figure 7: "Up-jumps" after additional deviation mechanisms.

Two-regime Modelling

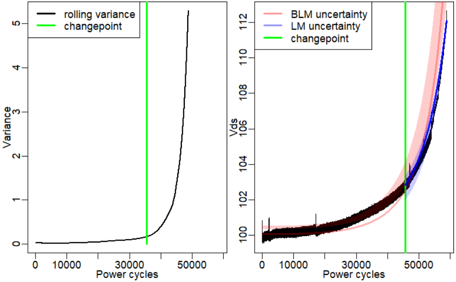

Figure 8: The proposed framework.

To capture degradation, we propose a heteroscedastic model that partitions the degradation process into two phases:

$$\sigma_t^2 = \begin{cases} \sigma_{high}^2 & \text{if } t < \tau_{cp}, \\ \sigma_{low}^2 & \text{if } t \geq \tau_{cp}, \end{cases}$$

where τ_{cp} represents the changepoint time.

Degradation Modelling

When only few degradation data are available, we use a Bayesian regression. For this, we apply normally distributed priors to the regression coefficients:

$$\beta_0 \sim \mathcal{N}(\mu_{\beta_0}, \sigma^2_{\beta_0}(t)),$$
$$\beta_1 \sim \mathcal{N}(\mu_{\beta_1}, \sigma^2_{\beta_1}(t)).$$

where μ_{β_j} and $\sigma^2_{\beta_j}$ are computed empirically.

By varying $\sigma^2_{\beta_j}$, the impact of the priors can be controlled:

- Initial: $\sigma^2_{\beta_i}(t) = 10^{-10}$ (highly informative).
- Evolution: Gradually increase to $\sigma^2_{\beta_i}$.
- Transition triggered by changepoint at τ_{cp}.

Polynomial regression

As more data is collected, we transition to a polynomial regression after the changepoint:

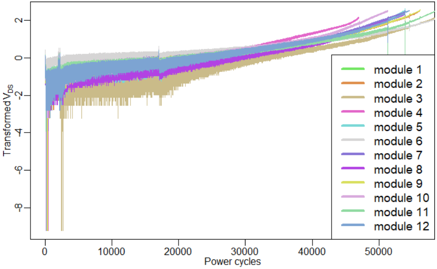

Figure 9: Data transformation.

First, a log-transformation is applied to V_{DS}:

$$y = log(V_{DS} - min(V_{DS}) + \phi),$$

with $\phi = \varepsilon_{log}$ is a correction term to avoid singularities.

Then, the cubic polynomial model of the form is used:

$$y = \beta_0 + \beta_1 t^3 + \varepsilon.$$

Polynomial regression contd.

For each new data point, we determine $\widehat{\beta}_0$ and $\widehat{\beta}_1$ based on the least squares criterion:

$$\min_{\beta_0, \beta_p} \sum_{i=1}^{k} \left(y_i - (\beta_0 + \beta_1 x_i^{\gamma})\right)^2,$$

where $k \in \{l, ..., n\}$, $l \leq n$, and $l, n \in \mathbb{N}$.

The Rolling Window Approach

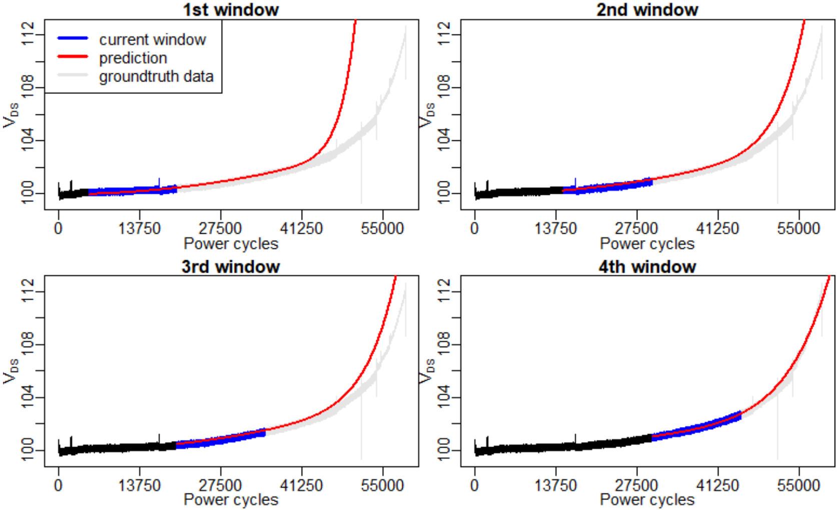

Figure 10: Window algorithm.

Multi-Technique Optimization Strategy

- **Heteroscedastic Variance Modeling**
  - Adaptive variance: $\sigma_t^2 = f(t, \tau_{cp})$.
  - Rolling window estimation: $\widehat{\sigma}_t^2 = \frac{1}{w}\sum_{i=t-w+1}^{t}(y_i - \widehat{y}_i)^2$.
- **Changepoint Detection**
  - $\tau_{cp} = \frac{\widehat{\sigma}_t^2}{\widehat{\sigma}_{tw_1}^2}$.
  - Triggers variance regime transition.
- **Asymmetric Uncertainty Bounds**
  - Lower bound: $\alpha_1 = 0.03$, Upper: $\alpha_2 = 0.07$.
  - Late failures reduced: $8.3\% \rightarrow 0.8\%$.

Handling Heteroscedasticity

- **Optimization is on the prediction error.**
- Adaptive Prediction Intervals combines parameter uncertainty, bias, and observation noise.

$$s_t^{*2} = \mathbf{x}_t^{*T} \mathrm{Cov}[\beta | y_{1:t}] \mathbf{x}_t^* + \widehat{\sigma}_t^{*2}.$$

- Weighted regression to improve accuracy of estimation of β.

Prediction Accuracy Comparison

Model	**20%**	**50%**	**90%**
Proposed model	-6409	-5306	**-1775**
log-Gamma GLM	-5693	12906	13996
inv-Gamma GLM	-6685	11658	14474
FB Prophet	NA	109882	22523
ARIMA	NA	173159	19378
GPR	NA	29390	6906

Key Achievements:

- 90% reduction in late failures.
- Best accuracy with minimal resources.
- Suitable for Edge-deployment.

Outlook

- Further accuracy improvement.
- Comparison of calculation resources of AI methods with the proposed method.
- Assess impact on qualification strategy.
  - Use of generic data.
  - End-of-life tests on generic family parts (reference parts)
  - Qualification tests to verify degradation paths (parts to be qualified).

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References I

"Siemens ag, the true cost of downtime 2024." https://assets.new.siemens.com/siemens/assets/api/uuid:1b43afb5-2d07-47f7-9eb7-893fe7d0bc59/TCOD-2024_original.pdf, 2024.
Accessed: 2026-06-11.

"Abb, value of reliability: Abb survey report 2023." https://search.abb.com/library/Download.aspx%3FDocumentID%3D9AKK108468A6878%26LanguageCode%3Den%26DocumentPartId%3D%26Action%3DLaunch, 2023.
Accessed: 2026-06-11.

S. Yang, A. Bryant, P. Mawby, D. Xiang, L. Ran, and P. Tavner, "An industry-based survey of reliability in power electronic converters," *Industry Applications, IEEE Transactions on*, vol. 47, pp. 1441 – 1451, 07 2011.

References II

Wikipedia contributors, "Power module — Wikipedia, the free encyclopedia," 2025.
[Online; accessed 11-June-2025].

Thank You!

