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Power Module Health monitoring in EV traction inverters

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Motivation about Lifetime Prediction Functionality (LPF)

Potential future EV traction inverter functionality

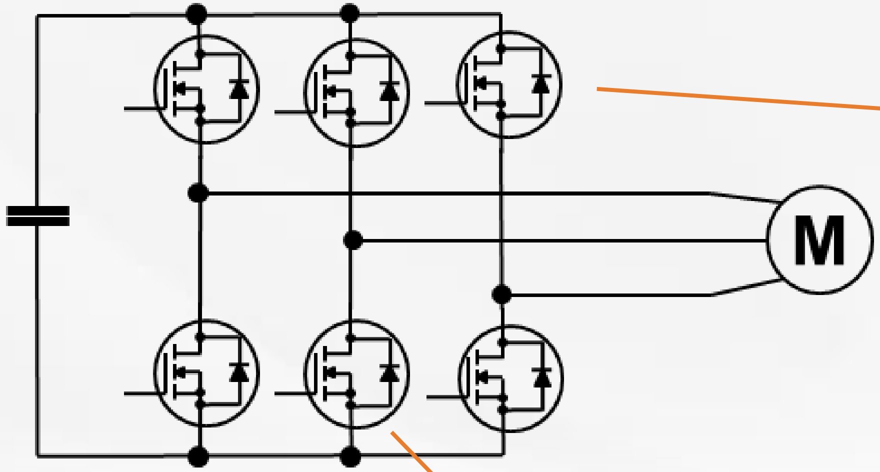
-> On the way from invention to innovation

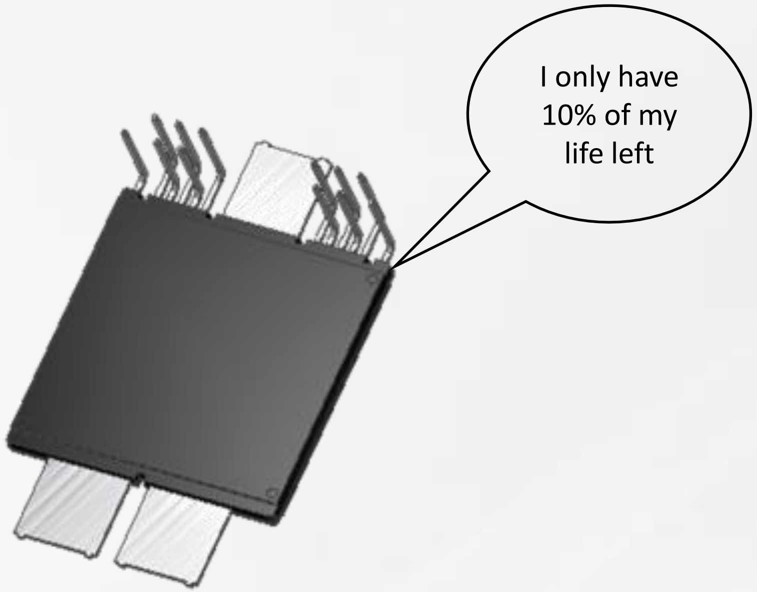
EV market is looking for low/mid cost EVs to address broad market

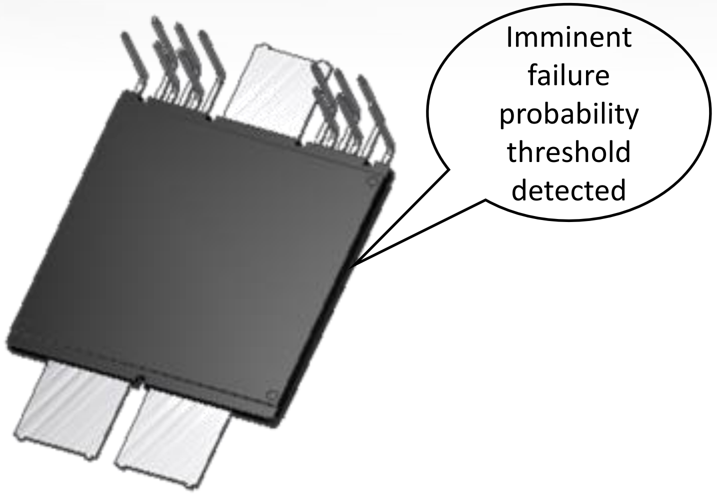
- LPF helps to lower (SiC) BOM cost
- Maintenance can be scheduled proactively
  - Predictive maintenance
- Reducing unexpected downtimes
  - Early detection of potential failures
  - Preventing catastrophic failures
- Enhanced reliability and safety
- Brings cost savings over the vehicle's lifespan

Lifetime Prediction Functionality (LPF)

Traction EV inverter simplified view







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Lifetime Prediction – Failure location/cause/indicator

Component Level

FAILURE LOCATIONS, CAUSES, AND INDICATORS OF SiC MOSFETS

Failure location	Failure Cause	Failure Indicator
Gate oxide	High electric field, high temperature	Gate leakage current I_{gss} [63], [75]
		Threshold voltage shift ΔV_{th} [44], [69]–[71], [114], [115]
		Drain leakage current I_{dss} [114], [116]
		Miller Plateau V_{gs_mp} [64]
Body diode	Forward bias [57], [58], [82]	Drain leakage current I_{dss} [59]
		Body diode forward voltage V_F [81]
Bond wires	Thermo-mechanical stresses	On-state drain-source voltage V_{ds_on} [103]
		Drain-source on-state resistance R_{ds_on} [104]
		Voltage between Kelvin, power sources [105]
		Bond wire resistance [87]
Solder layers		Thermal resistance R_{th_jc} [112]
		Solder layer resistance [106]

Failure location

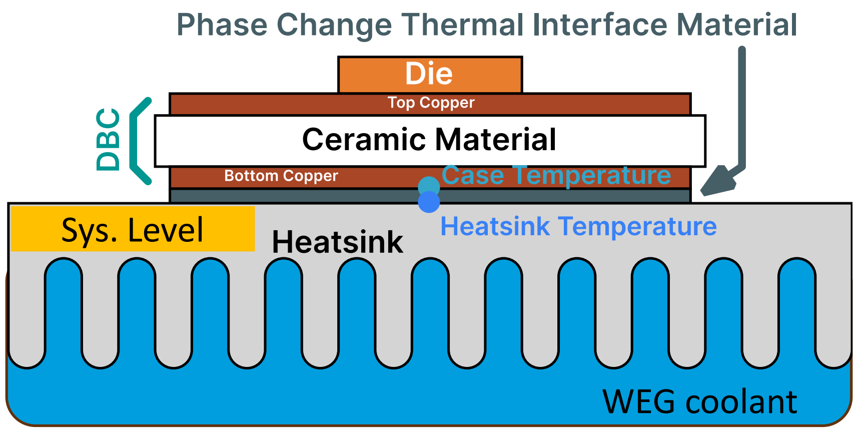
Failure Cause

Failure Indicator

Accelerated Lifetime test

COMPARISON OF DIFFERENT ALTs

Test	Test condition		Test location	Failure indicator
HTGB	V_{gs} stressed to maximum voltage at maximum T_j		Gate oxide	I_{gss}
				V_{th}
HTRB	V_{ds} reversely biased to the maximum voltage at maximum T_j		Edge channel structure and solid-state junction surface	I_{dss}
PC	The device is heated and cooled by pulses		Bond wire	V_{ds_on} / V_F
				V_{th}
				R_{ds_on}
				I_{gss}
				C_{ds}
TC	External heat and cooling	Short cycle time	Solder joint, bond wire	R_{ds_on}
TS		Long cycle time	Interface between DCB and baseplate	R_{th_jc}



Real application with Thermal stack up WEG coolant

Source IEEE: Z. Ni, et al.: Overview of Real-Time Lifetime Prediction and Extension for SiC Power Converters
https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8944162

Component-Level Lifetime Models

TABLE IV
SUMMARY OF SiC MOSFET COMPONENT-LEVEL LIFETIME MODELS

Coffin-Manson do not cover gate oxide breakdown

Model Categories	Failure Modes	Model Descriptions	Features
Physics of failure models	Gate oxide breakdown	Stressed and normal voltage based	Suitable for long-term damage behavior prediction
		Weibull-Arrhenius exponential model and its derivatives	Capable of modeling temperature stress
	Bond wire fracture	Schafft Model	Capable of modeling wire bending stress
	Bond wire lift-off	Coffin-Manson model	Fails to consider the impact of T_{j_mean}
		Coffin-Manson model by Arrhenius approach	Shows SiC MOSFETS achieve more cycles to failure than Si IGBTs, especially at low ΔT_j
		Bayerer model	Includes power-on time t_{on}, current I_w, blocking voltage V_B, and wire diameter D_w
		Plastic strain based Coffin–Manson model	Capable of modeling CTE mismatch between the bond wire copper and SiC
	Solder fatigue	Coffin-Manson model by Arrhenius approach	Capable of including the impact of T_{j_mean}
		Plastic strain based Coffin–Manson model	Capable of modeling CTE mismatch between the DCB-die solder attach and SiC
		Norris–Landzberg model	Considers TC frequency and maximum temperature
		Creep strain energy	Shows exponential relationship between lifetime and creep strain energy in a cycle
	Failure modes indicated by R_{ds_on}	Exponential function for R_{ds_on}	Covers more than one failure mode

Source IEEE: Z. Ni, et al.: Overview of Real-Time Lifetime Prediction and Extension for SiC Power Converters
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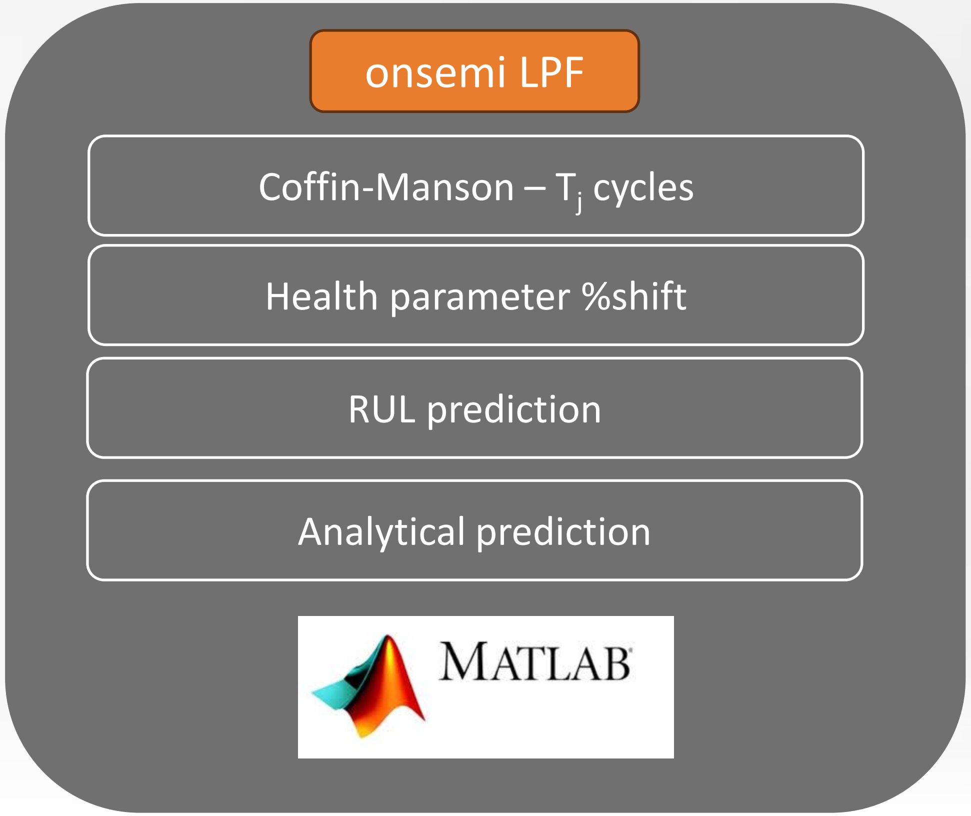
Lifetime prediction models

- Analytical-based
  - predicts lifetime based on equations describing the system
- Data-driven
  - predicts using a historical database of measured devices
- Hybrid models
  - combine different models



onsemi Lifetime Prediction functionality

- Coffin Manson model

$$N_f = K * \Delta T^{-\beta_1} * e^{\beta_2/(273+T_{j,max})} * t_{on}^{-\beta_3}$$

$$D = \sum_{i=1}^{N} \frac{n_i}{N(\Delta T, T_m)}$$

- Lifetime parameter % shift from initial value
  - R_{th} – 20% thereshold
  - $R_{ds\text{-}on}$ – 5% threshold
- Remaining Useful Lifetime (RUL) prediction
  - Training on collected data till failure
- Analytical prediction model
  - Proprietary model

- onsemi LPF training with real data
- Matlab access to database to train model and optimize

Methodology and its phases to get data to train LPM model for the end application

Data collection starts at semiconductor manufacturer side, ends at customer side.

- Four phases ensure robustness of LPM model for end application
- Phase 1 and 2 target any packaging-related issues
- Phase 3 and 4 emulates end application use case

Phase no.	Test Method	LPM model parameters	Test description, conditions
1.	AQG324 Packaging Level Testing	V_{th} – Gate threshold voltage T_j – Junction temperature $R_{DS\text{-}ON}$ – Power switch ON resistance	DC current
2.	Inverter Mode Inductive Load Testing		Inv. Mode – PWM drive, inductive load
3.	Motor Emulator Testing		EV motor load, PWM driving, driving profile
4.	Product Qualification Testing		Product qualification testing

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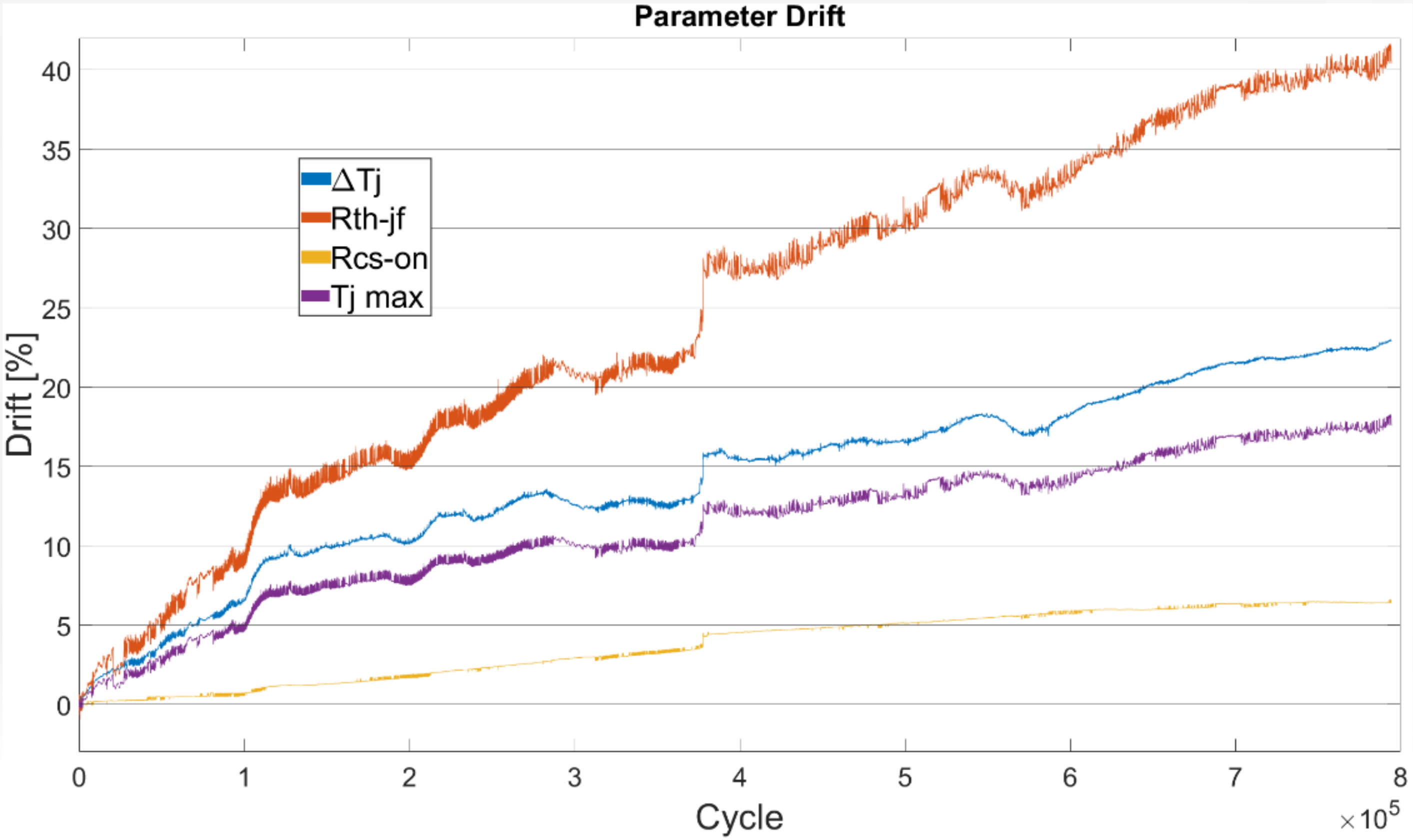
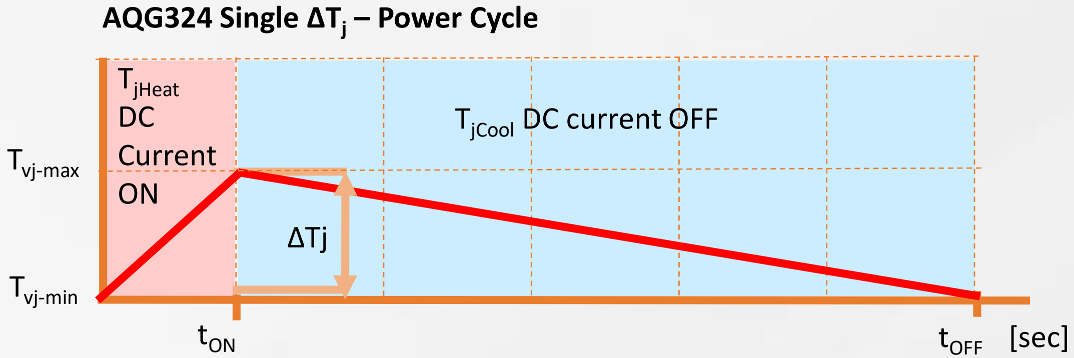
AQG324 Power Cycle test - IGBT data collection example





Coffin Manson – T_j cycle lifetime consumption

$$N_f = K * \Delta T^{-\beta_1} * e^{\beta_2/(273+T_{j,max})} * t_{on}^{-\beta_3}$$

$$D = \sum_{i=1}^{N} \frac{n_i}{N(\Delta T, T_m)}$$

- MOSFET/IGBT Junction temperature DC current (constant) T_j cycling – accelerating lifetime usage/package level test
- Collected parameters at AQG324 testing to get data for LPM, IGBT example: V_{th}(not shown), $V_{ce(sat)}$, R_{th-jf}, T_{j-max}, ΔT_j

EOL criteria – change from initial value

- $V_{ce(sat)}$ (IGBT) or V_{DS} (SiC Mosfet) -> 5%
- R_{th-jf} -> 20%

-> For our test purpose tested till failure to get data till failure suitable form RUL model training

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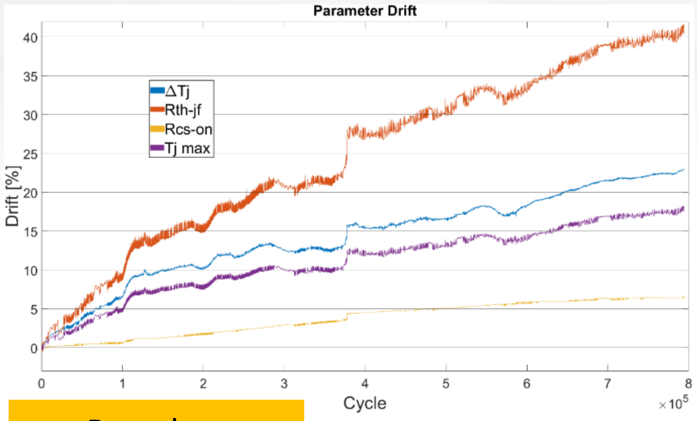
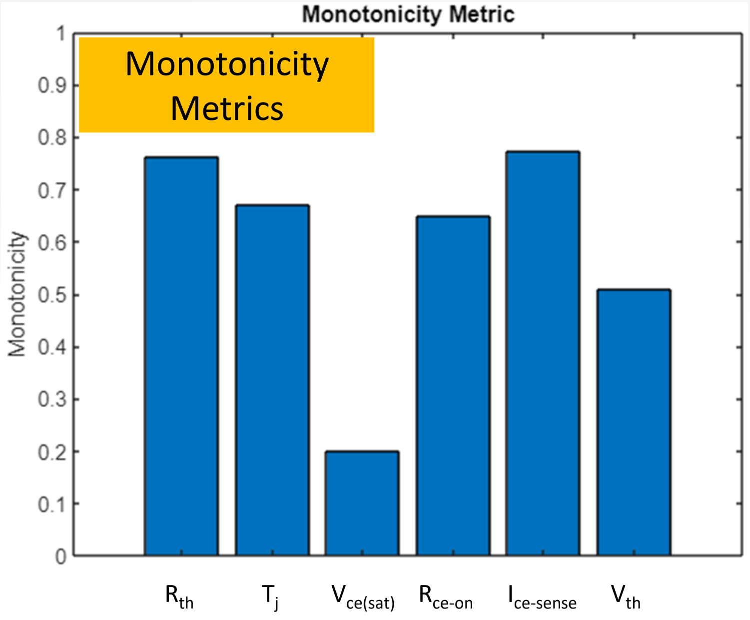
Lifetime parameters verification and selection

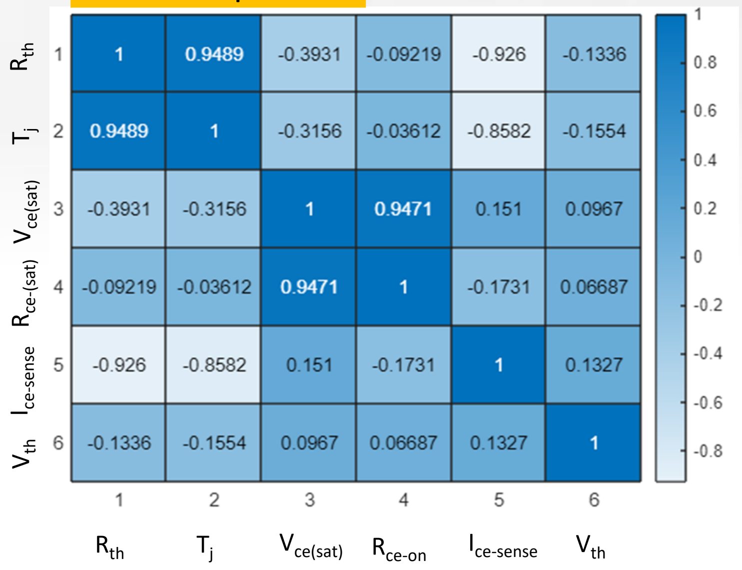
1. Statistical verification of collected data
    - Monotonicity metric (Quantify monotonic trend in condition indicators)
    - Prognosability metric (Measure of variability of condition indicators at failure)
    - Trandability metric (Measure of similarity between trajectories of condition indicators)
2. Measured parameters – Correlation heatmap
    - Select not corelated parameters (fewer input parameters for RUL model) – T_j, V_{th}, $R_{ds\text{-}on}$ (SiC Mosfet), $V_{ce(sat)}$ (IGBT)
3. PCA analysis – Principal component analysis of raw data – get Health Indicator



Raw data



Correlation Heat Map

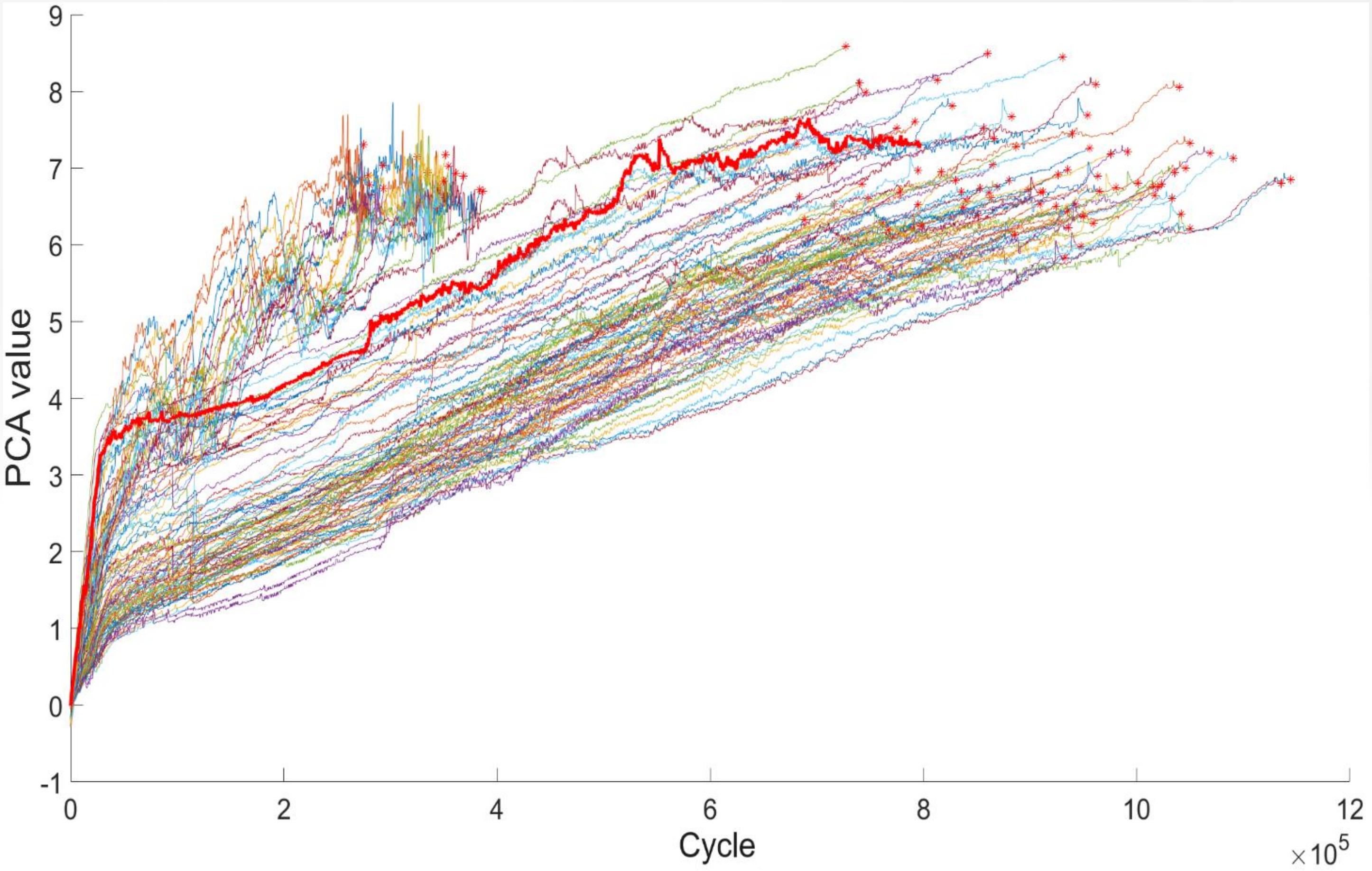


DUT measured data → Statistical verification Mon., Prog., Trand. → Correlation Heat Map → PCA analysis (Health indicator)

RUL model selection and testing approach

Selected data-driven RUL model

- Selection of uncorrelated lifetime parameters
- Monotonicity, Prognosability and Trendability
- Principal Component Analysis (PCA) technique
- **Predictive model: Pairwise Similarity Model**
- RUL model optimization: Matlab Test Automation
- Performance tested with measured data till failure
- Prediction model testing with incomplete data set (e.g. 50%, 70%) of data measured till failure
  - Get RUL model prediction accuracy
- Quantify prediction accuracy



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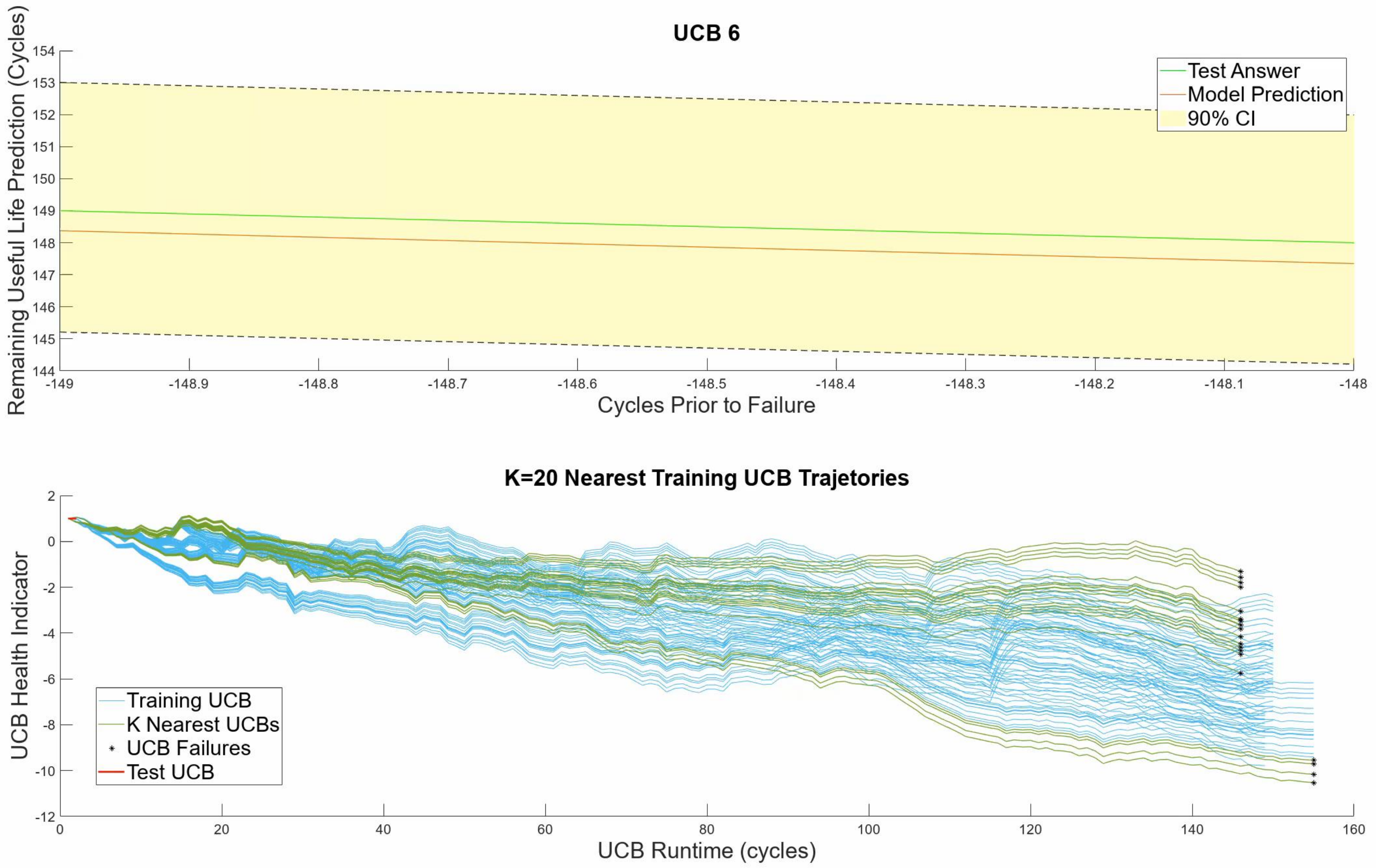
RUL model remaining cycles prediction - test example



Test Answer

- Training data – database
- Known RUL trajectory

Model prediction

- Predicted Remaining Cycles
- RUL Prediction

90% Confidence interval

- Confidence interval

Automatic optimization of RUL model settings

Raw data

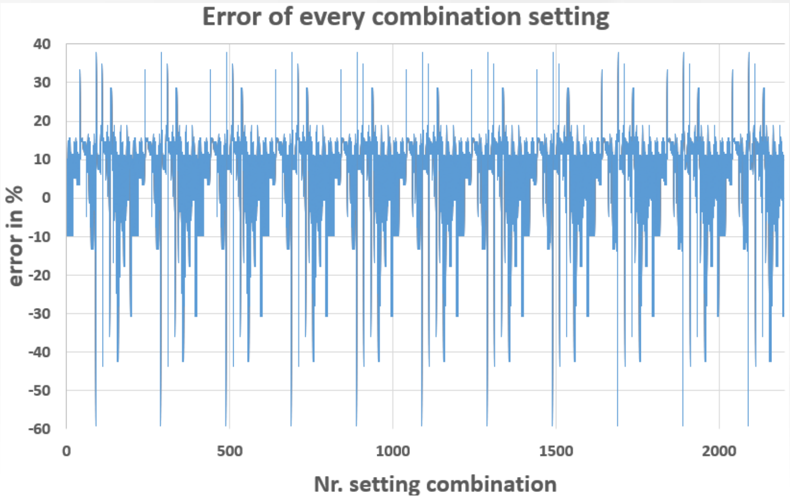
Data processing, filtering, decimation

PCA analysis

RUL Model

Experiment Manager

Trial	Method	Neighbor	History	Range	estRUL_output
1	correlation	10	10	0	272004
2	dtw	10	10	0	307829
3	correlation	20	10	0	272004
4	dtw	20	10	0	327268
21	correlation	10	20	0	409805
22	dtw	10	20	0	307747
23	correlation	20	20	0	409805
24	dtw	20	20	0	327224
41	correlation	10	30	0	418288
42	dtw	10	30	0	307612
43	correlation	20	30	0	418288
44	dtw	20	30	0	327147
201	correlation	10	10	0.1	272004
202	dtw	10	10	0.1	307829
203	correlation	20	10	0.1	272004
204	dtw	20	10	0.1	327268
221	correlation	10	20	0.1	409805
222	dtw	10	20	0.1	307747
223	correlation	20	20	0.1	409805
224	dtw	20	20	0.1	327224
601	correlation	10	10	0.3	272004
602	dtw	10	10	0.3	307829
603	correlation	20	10	0.3	272004
604	dtw	20	10	0.3	327268
2197	correlation	90	100	1	391149
2198	dtw	90	100	1	381669
2199	correlation	100	100	1	391149
2200	dtw	100	100	1	381669



Experiment Manager:
automatic test to optimize RUL model settings for available database to get best prediction accuracy.
See Trials column – no. of tests

RUL model settings results

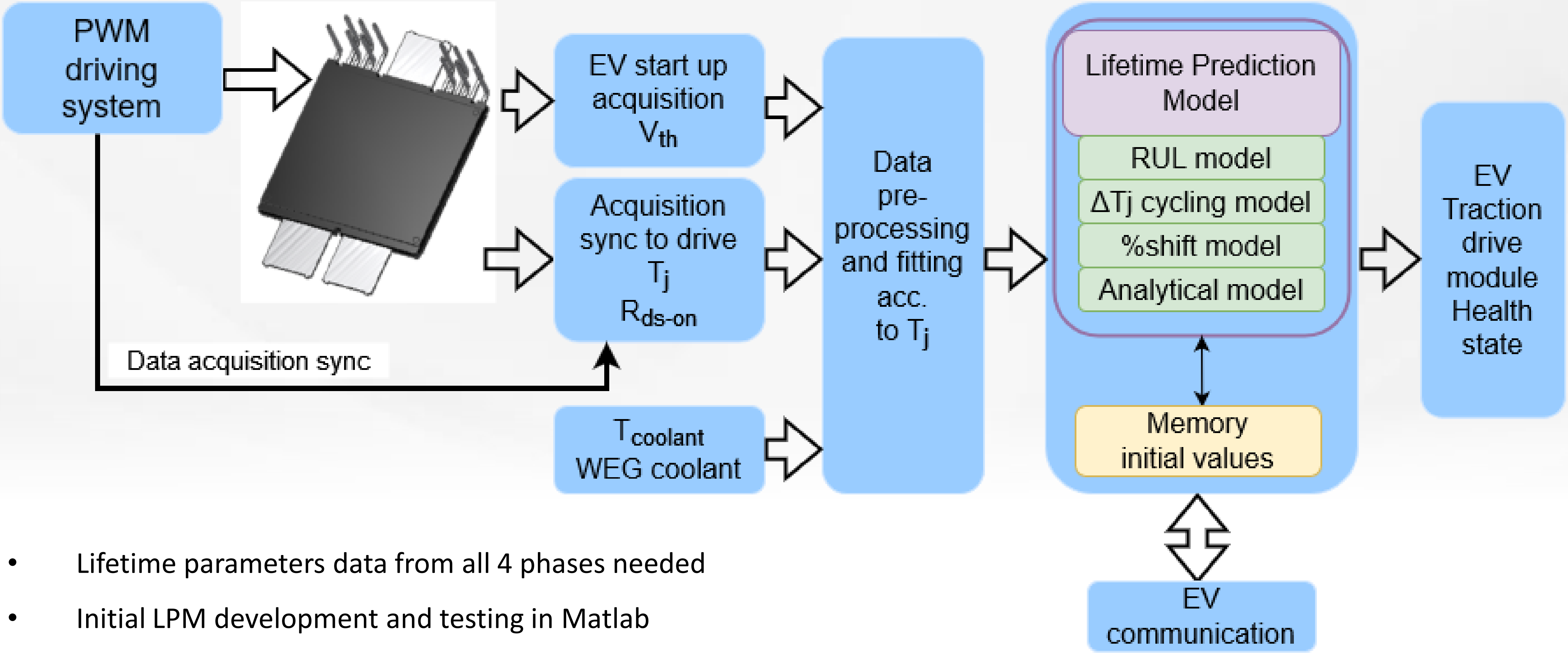
DUT 50%	Trial	Method	Distance	Neighbor	History	Estimated RUL	Real remaining RUL	Percentage error
6	81	correlation	euclidean	10	50	429614	431661	-0.474
	101	correlation	euclidean	10	60	431387	431661	-0.063
	129	correlation	euclidean	50	70	426633	431661	-1.165
	131	correlation	euclidean	60	70	428761	431661	-0.672
	183	correlation	euclidean	20	100	426229	431661	-1.258
11	81	correlation	euclidean	10	50	436909	442767	-1.323
	151	correlation	euclidean	60	80	437532	442767	-1.182
	163	correlation	euclidean	20	90	439208	442767	-0.804
	165	correlation	euclidean	30	90	439289	442767	-0.785
	167	correlation	euclidean	40	90	436452	442767	-1.426
	169	correlation	euclidean	50	90	439667	442767	-0.700

DUT 70%	Trial	Method	Distance	Neighbor	History	Estimated RUL	Real remaining RUL	Percentage error
1	101	correlation	euclidean	10	60	286194	289530	-1.152
6	88	dtw	euclidean	40	50	258487	258997	-0.197
6	188	dtw	euclidean	40	100	258550	258997	-0.173
11	189	correlation	euclidean	50	100	265569	265660	-0.034

DUT 90%	Trial	Method	Distance	Neighbor	History	Estimated RUL	Real remaining RUL	Percentage error
1	65	correlation	euclidean	30	40	93148	96510	-3.484
6	81	correlation	euclidean	10	50	85552	86332	-0.903
11	171	correlation	euclidean	60	90	87834	88553	-0.812
	173	correlation	euclidean	70	90	87535	88553	-1.150
	175	correlation	euclidean	80	90	87535	88553	-1.150
	177	correlation	euclidean	90	90	87535	88553	-1.150
	179	correlation	euclidean	100	90	87535	88553	-1.150

- Tested various levels of traction inverter module usage – 50%, 70%, 90%
- Real remaining RUL – real no. of T_j cycles from tested data till failure
- Estimated RUL – number of T_j cycles till failure estimated by optimized RUL model

Proposed - LPM Implementation in Traction Inverter



- Lifetime parameters data from all 4 phases needed
- Initial LPM development and testing in Matlab
    - Linked to Lifetime parameters database
- LPM to consists of 4 different models
- LPM model code to C or HDL

Conclusion

- Key lifetime prediction parameters presented
  - V_{th}, T_j, $R_{DS\text{-}ON}$
- Presented lifetime parameters selection and RUL model testing
- LPM requires combination of various prediction models
  - Tj cycle based, % shift, RUL model and analytical model
- Robust LPM requires lifetime prediction parameters data collection starting at semiconductor manufacturer side and finishing at customer (application side)

Thank You

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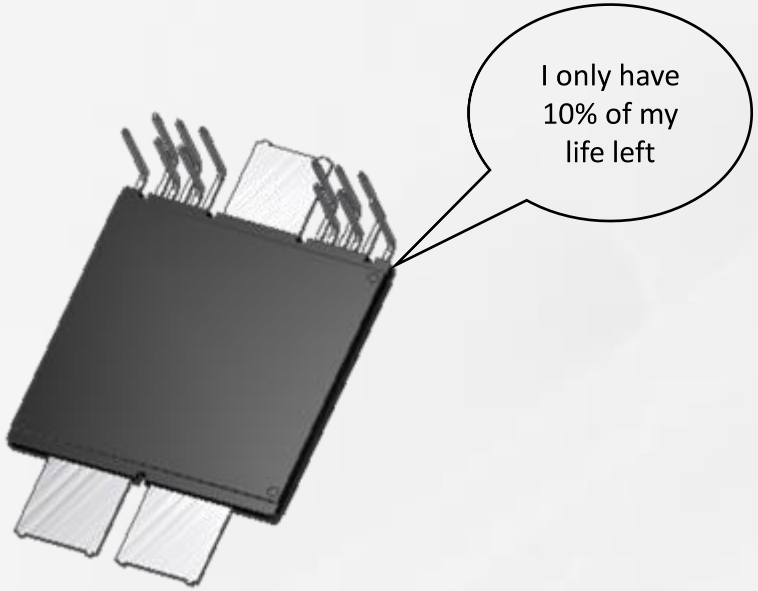
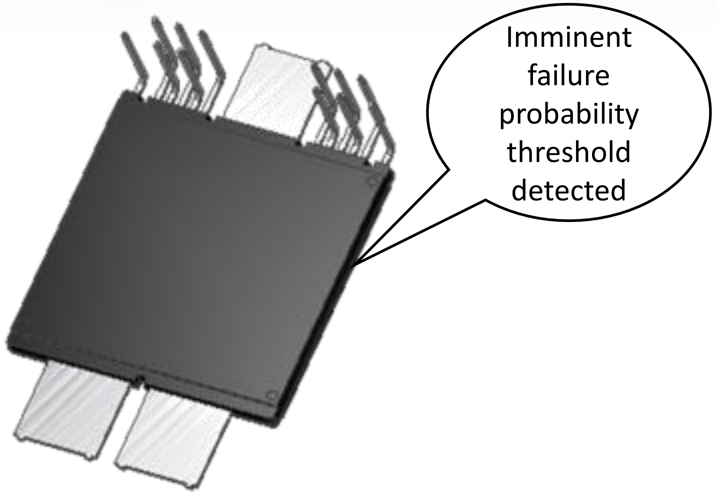

I only have
10% of my
life left


Imminent
failure
probability
threshold
detected