The Santa Clara Valley (Silicon Valley) Chapters:

Making digital twin work

Prof. G.Q. Zhang (g.q.zhang@tudelft.nl)

Prof. J.J. Fan, Prof. W. van Driel, Prof. X.J. Fan

Delft University of Technology, The Netherlands

Visit:

attend.ieee.org/repp

Short Bio

- Chair professor for Micro/nanoelectronics system integration and reliability, Delft University of Technology; IEEE Fellow; Secretary general of IEEE ITRW

- Philips Research Fellow until May 2013; NXP Senior Director for technology strategy until 2009

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Outlines

- Motivation
- State-of-Art
  - Material modeling and characterization
  - Process design and modeling
  - Tests and Qualifications
  - Health monitoring and lifetime prognostics
- Challenges and Roadmap
- Summary

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Autonomous driving

Source: www.ibeo-as.com

Intelligent manufacture

Source: www.ptc.com

AI for X

Smart city

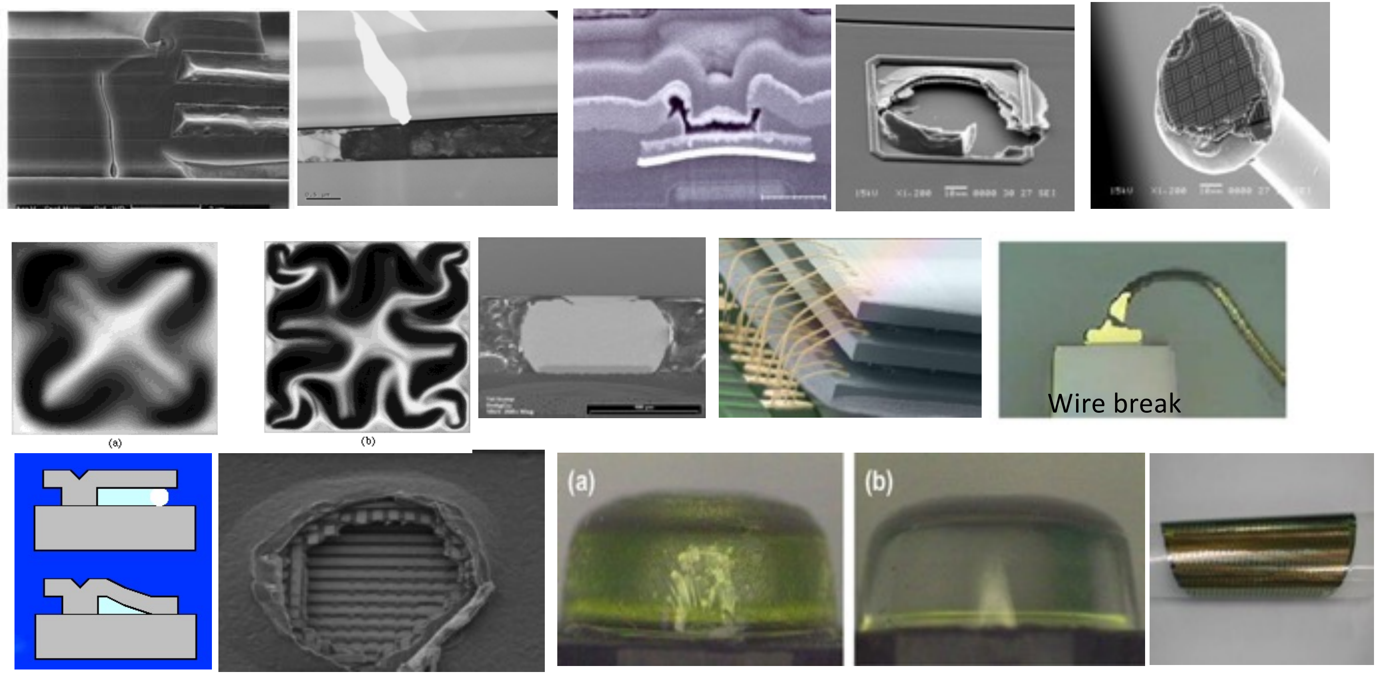
Source: mashdigi.com

Smart service

Source: www.jeanhillstudios.com

Reliability: The major concern of high-tech industries

Warranty claims: 2% of global annual industrial revenue;
delayed product release; liability; reduced consumer confidence



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Business consequences

Warranty claims US companies

Company	2009 Accruals in Mio $	2009 Claims Rate (% of sales)	2008 Claims Rate (% of sales)	2007 Claims Rate (% of sales)
Lexmark International	84	9.0%	8.4%	13.0%
Garmin Ltd.	165	5.6%	3.8%	
Hewlett-Packard Co.	2,701	3.6%	3.7%	2.9%
Eastman Kodak	88	3.2%	1.9%	
Whirlpool Corp.	396	3.0%	2.8%	3.8%
Caterpillar Inc.	880	3.0%	2.6%	2.2%
IBM Corp.	374	2.3%	2.0%	2.8%
Dell Inc.	995	2.3%	2.0%	2.2%
Microsoft Corp.	148	2.1%	2.4%	6.2%
Black & Decker Corp.	92	1.9%	2.0%	1.8%
Ford Motor Co.	1,561	1.5%	1.7%	2.6%
Cisco Systems	381	1.5%	1.2%	
Motorola Inc.	301	1.4%	1.5%	2.0%
Harley-Davidson Inc.	51	1.3%	1.0%	1.2%
Apple Inc.	303	1.0%	0.9%	1.0%
General Electric Co.	780	1.0%	1.2%	0.8%
Johnson Controls	257	1.0%	0.8%	
Honeywell International	188	0.8%	0.8%	0.7%
Boeing Co.	167	0.5%	0.5%	0.7%

Source: SEC, via Warranty Week

NA: www.recalls.gov

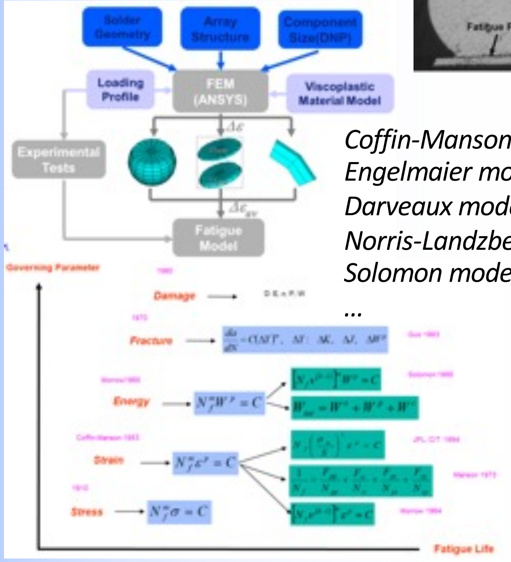
Past solutions with handbooks

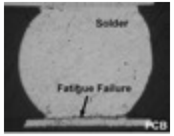
Since 1960s, several reliability prediction handbooks have been published, with applications in Aviations and Defenses, Telecommunications, Automotives, Electronics and Computers, and Mechanical Equipments.

Past solutions with empirical models

Arrhenius Model, Eyring Model, Voltage/Field Effect Model, Current Model, Power Model, Temperature Cycling Models, Humidity Models…

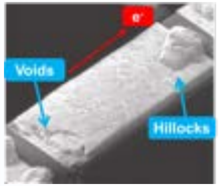
Solder fatigue models





Coffin-Manson model
Engelmaier model
Darveaux model
Norris-Landzberg model
Solomon model
…

Electromigration model

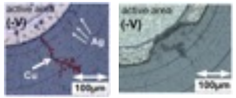


Black's model

$$\frac{1}{\mathrm{MTF}} = Aj^n \exp\left(\frac{-\phi}{kT}\right)$$

where MTF, median time to failure (hrs), *A* pre-factor constant, *j* current density (A/m²), ϕ activation energy (eV), *k* Boltzmann constant (J/K), *T* temperature (K)

Humidity driven failure models



ISPSD **2015, 385-388**

Lawson model: $t_f = A\cdot e^{\Delta E/kT} e^{bRH^2}$

Eyring model: $t_f = A\cdot e^{\Delta E/kT} e^{B\cdot RH}$

Peck-Zierdt model: $t_f = A\cdot e^{[\Delta E/kT + B(\ln RH)]}$

Reich-Hakim model: $t_f = Ae^{[B(T-273)+RH]}$

Weick model: $t_f = A\cdot e^{\Delta E/kT}\cdot e^{(B\cdot T/RH)}\cdot e^{(C\cdot RH)}$

…

where RH= relative humidity

- Need comprehensive knowledge of failures
- Can't consider the field's uncertainties and dynamics
- Require significant time and operation cost, experience based

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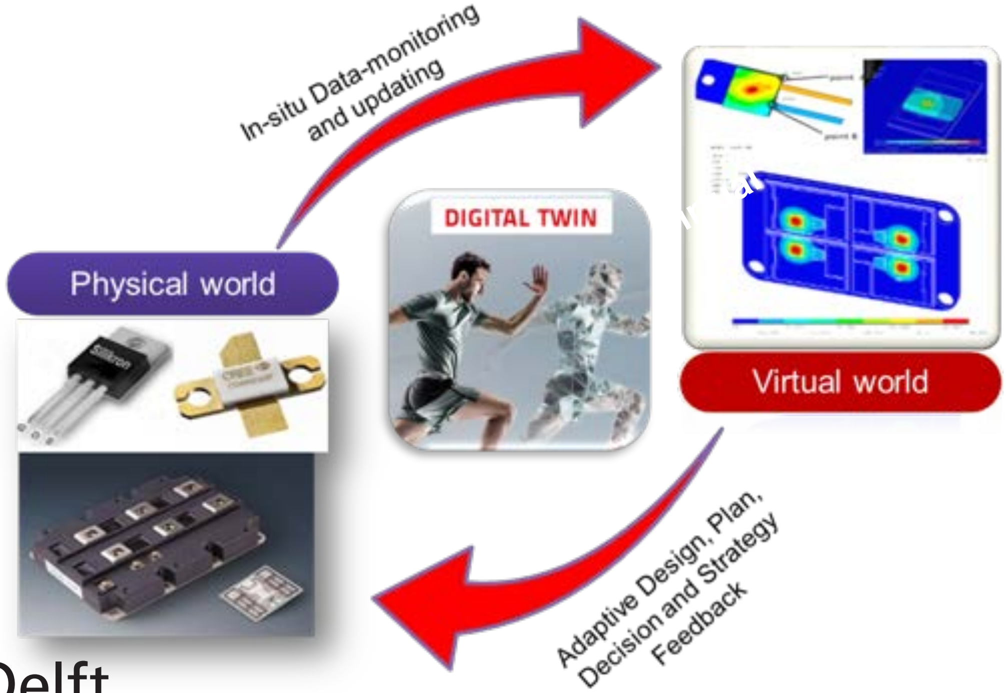
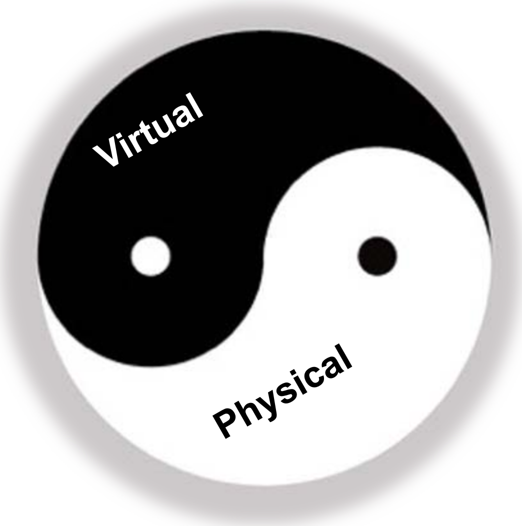
Digital Twin for Mission Critical Electronics (MCE)

- **MCE** grows fast
- “**Performance and lifetime on demand”** becomes essential
- DT will be the key enabler

Digital Twin (DT) contains 3 main parts:

- **Physical products/systems** in Real Space, i.e. **materials, products, processing, operation, recycle…**
- **Virtual products/systems** in Virtual (digital) Space, i.e., simulation models…..
- **Connectivity** of data, information and instruction that connect the virtual and real worlds together



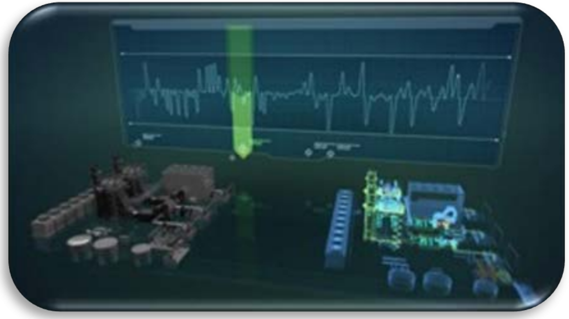


3 Connectivity Scenarios (combination is also possible)

Weak connection

- Modeling as a supporting tool
- No closed loop
- Virtual prototyping
- Product and process design

Cloud connection



- Real-time monitoring/data filtering/transmission
- Cloud platform, complicated simulation models, cloud computing
- Output filtering, intelligent control
- Separated closed loop

Embedded connection

- Real-time monitoring/data filtering/transmission
- Highly reliable DT chip (or embedded in MCU), with built in simpler/compact models and edge computing
- Integrated close loop, control & decision-making

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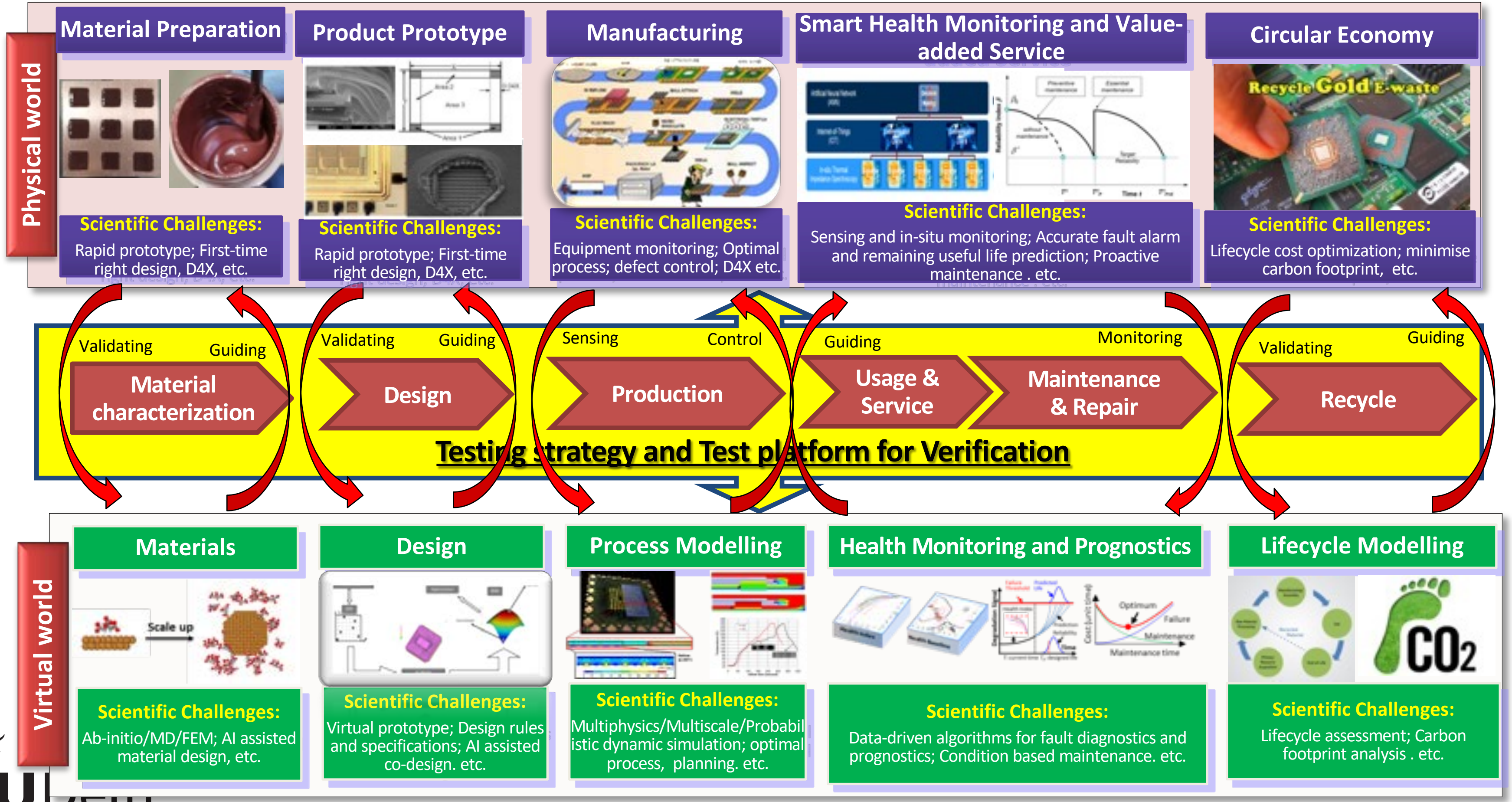
The Landscape of Digital Twin



Source: Kouchi Zhang & Jiajie Fan, Heterogeneous Integration Roadmap

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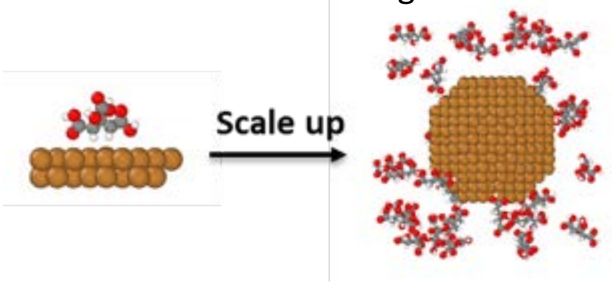
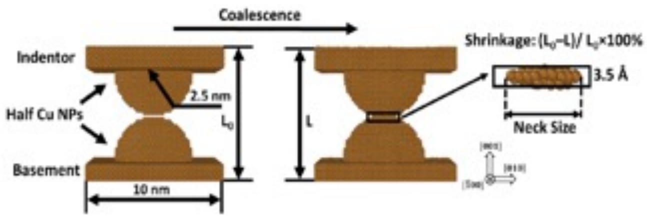
Material modeling and characterization: NanoCu

MD assisted Material design and modeling

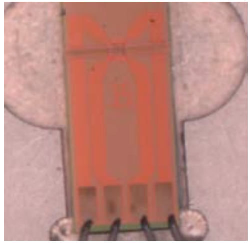
- Anti-oxidation coating



- Sintering mechanism
  Impact of ***P***, ***T***, ***t***, etc.

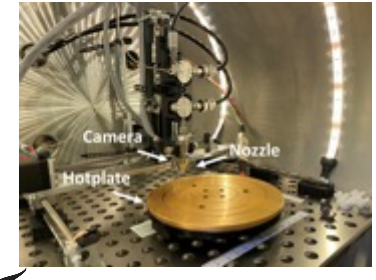


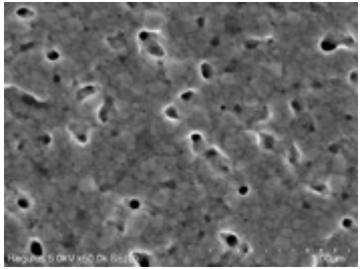
- MEMS micro-hotplate based time-resolved in-situ SEM



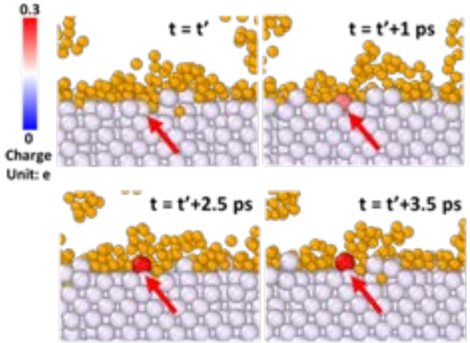
MD assisted property characterization

- Electromigration

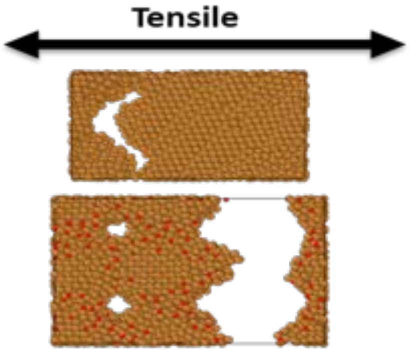




- Sulphidation



- Oxidation



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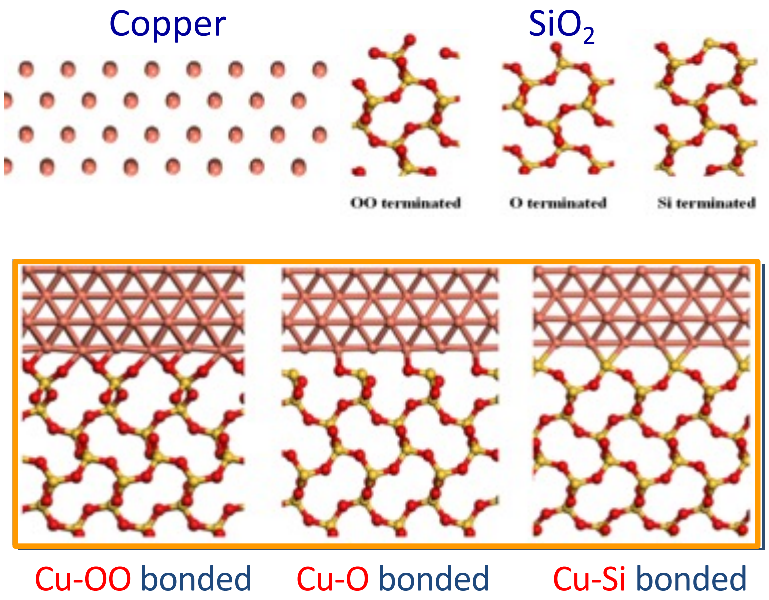
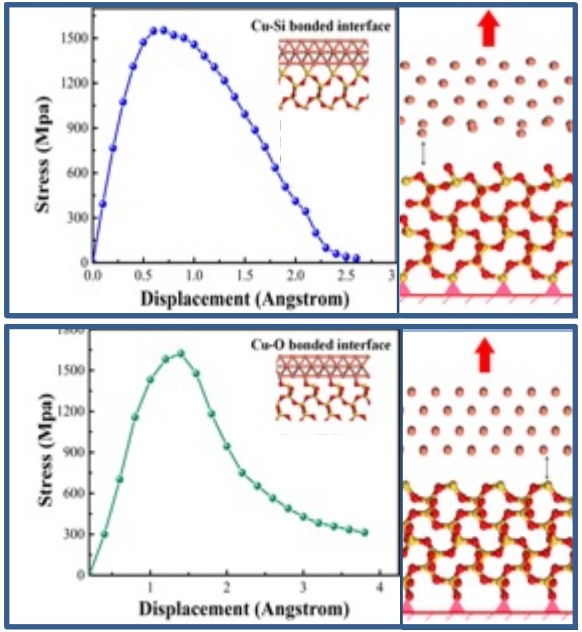
Material modeling and characterization: Cu/SiO2 interface

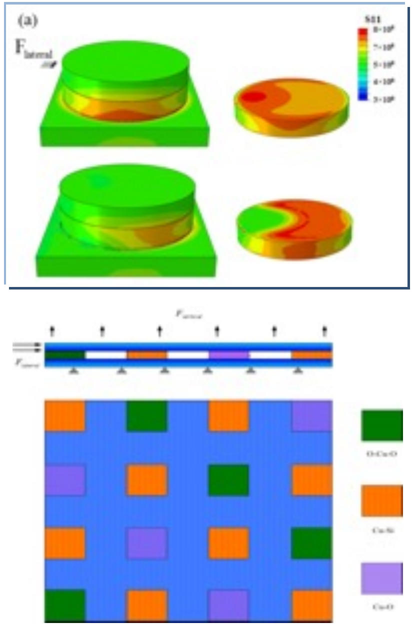
Multiscale modeling from First principles simulation to molecular dynamics simulation to finite element modeling



First principles simulation



Molecular dynamics simulation

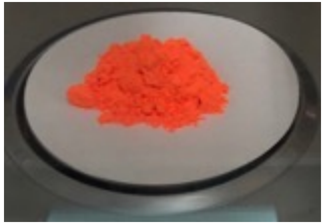


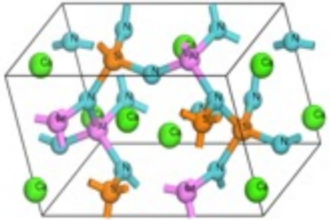
Finite element simulation

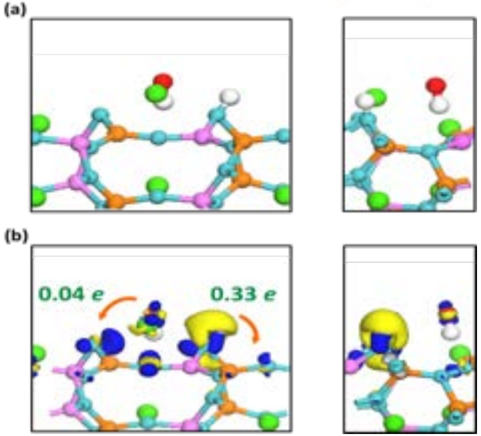
Z Cui, X Chen, X Fan, GQ Zhang, Interfacial Properties of Cu/SiO2 using a Multiscale Modelling Approach in Electronic Packages, EuroSimE 2018.

Material modeling and characterization: Phosphors

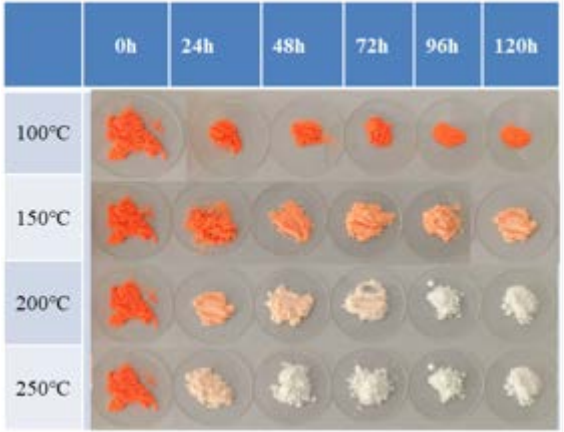
Ab-initio/First principle modeling of hydrolysis mechanism for R6535 $CaAlSiN_3:Eu^{2+}$ red phosphor

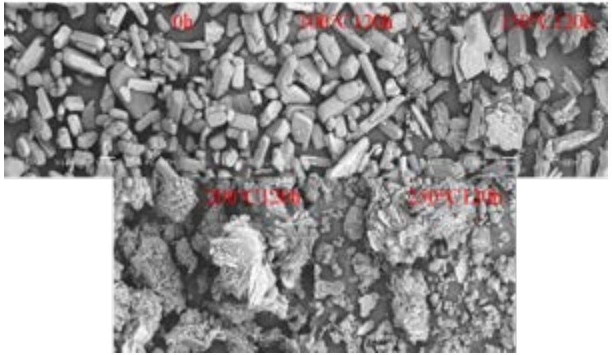






First principles simulation





$$CaAlSiN_3(s)+2H_2O(l)\rightarrow Ca^{2+}+2OH^{-}+H_2AlSiN_3(s)$$

Moisture driven degradation of $CaAlSiN_3:Eu^{2+}$ red phosphor can be attributed to the **initially dissolved of Ca^{2+} and OH-**, gradually **crashed crystallinity of host lattice and the increased surface roughness** from reaction residues.

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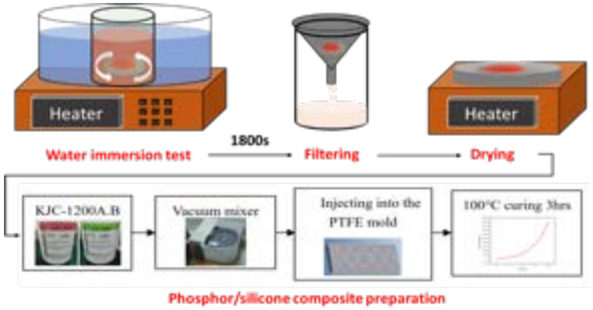
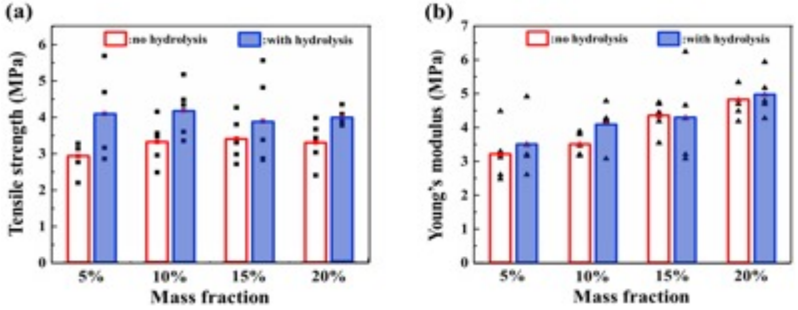
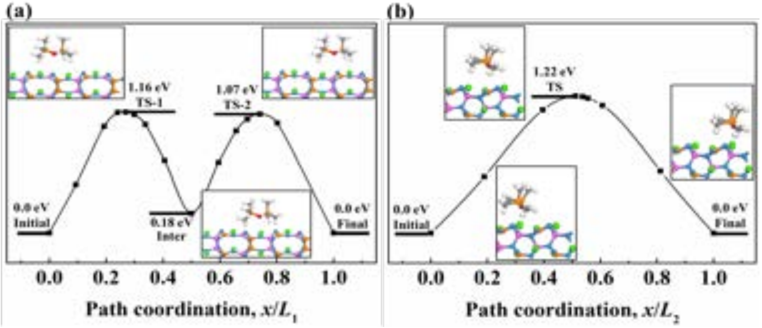
J. Fan, G.Q. Zhang et al. ***Journal of Luminescence*** *219, 116874, 2020*

Material modeling and characterization: Phosphor/silicone interface

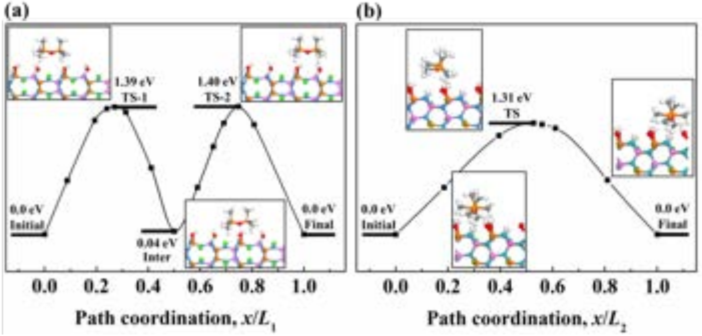
Ab-initio/First principle modeling of mechanical properties for Phosphor/silicone interface







Pristine $CaAlSiN_3$[010] surface, the minimum-energy pathway along (a) [100] direction. (b) [001] direction.



Hydrolyzed $CaAlSiN_3$[010] surface, the minimum-energy pathway along (a) [100] direction. (b) [001] direction.

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Z. Cui, J. Fan, G.Q. Zhang et al. ***Applied Surface Science*** *510, 145251, 2020*

MD based low-k material/interface design

Motivations

- Develop/design reliable low-k material and interface
- Using molecular dynamics to model the nanoscale material and interface

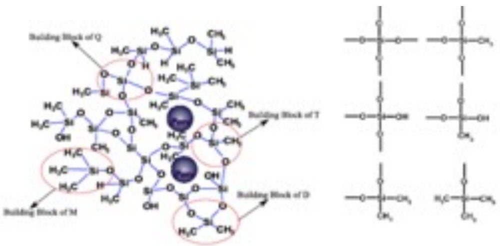
Scientific challenges

- Modeling

-Amorphous and porous material

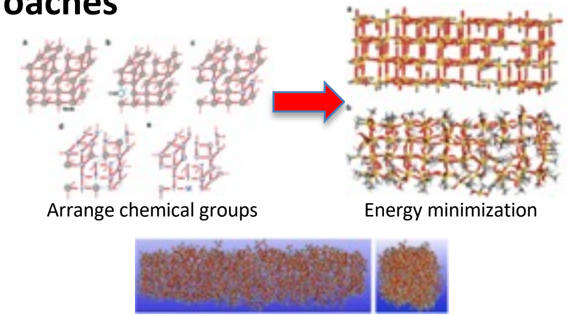
-Chemical bonding status at interface

- Experimental comparison



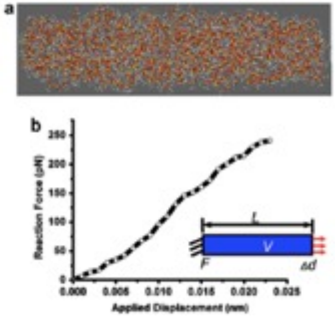
Molecular simulation strategy for mechanical modeling of amorphous/porous low-dielectric constant materials. Appl. Phys. Lett. 92, 2008

Approaches

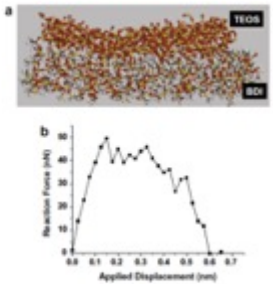


Results

- Prediction of mechanical properties of low-k material



- Prediction of interfacial strength of low-k material



Example: Molecular dynamics analysis for multi-scale reliability assessment of CNTs

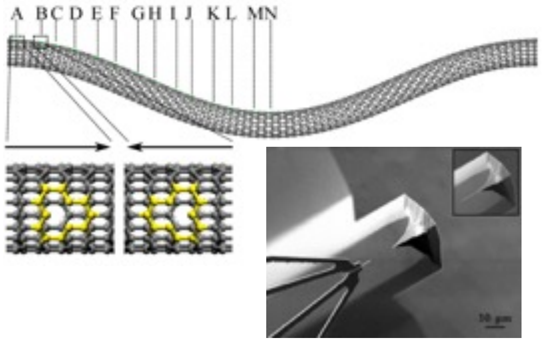
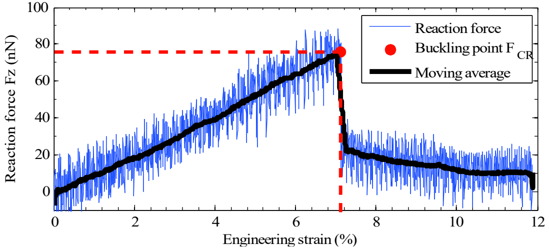
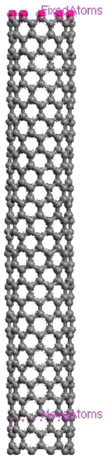


Image: Özlem Sardan, DTU





Problem

- Mechanical stability of CNTs will affect the reliability and performance

Scientific challenge

- Computational studies overcome the limitations of experimental approaches and give extra control on parameters such as defect position

Results

- Defects near the deflection points of the CNT, reduce the critical buckling load (about 70%) at low temperature
- Defects do not significantly alter the critical buckling load at room temperature

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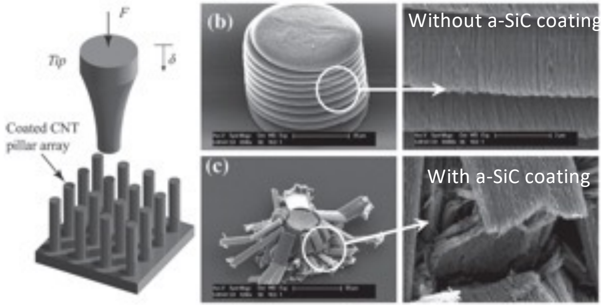
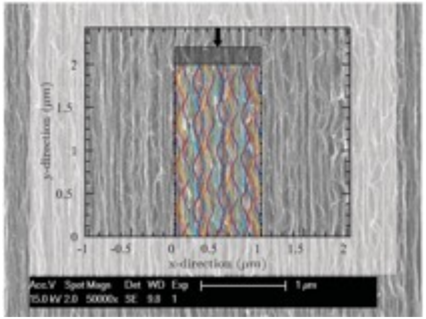
Effects of single vacancy defect position on the stability of carbon nanotubes,
Journal of Microelectronics Reliability, ***52, (2012)***

Material modeling and characterization: CNT pillars

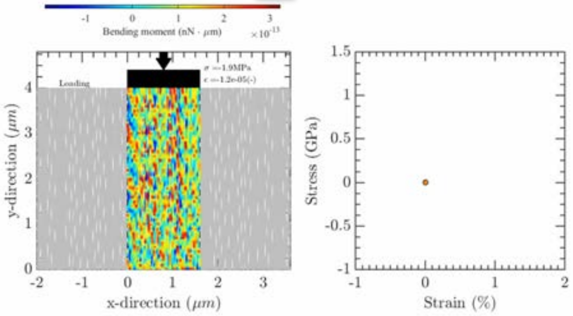
Multiscale modeling of failure modes for CNT pillar with and without a-SiC coating



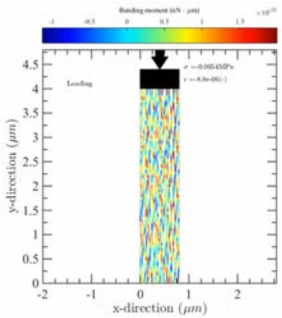
Macroscale phenomena: Different failure modes of CNT pillar with and without a-SiC coating



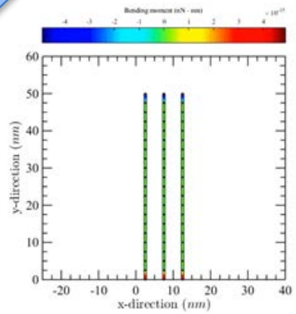
Simplified simulation model



Macroscale simulation



Microscale simulation

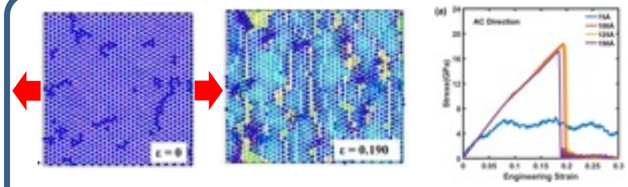


Nanoscale simulation

Adv. Funct. Mater. ***2016***

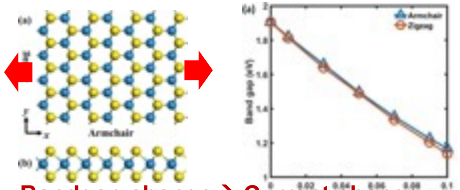
Material modeling and characterization: WS_2 sensor

Effects of Defect and Temperature on the Mechanical Performance of WS_2: A Multiscale modeling



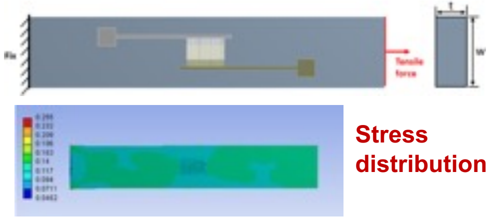
Defects
Temperature → Young's modulus, Fracture strain, Ultimate stress

Molecular dynamic analysis (MDA)



Bandgap change→ Current change

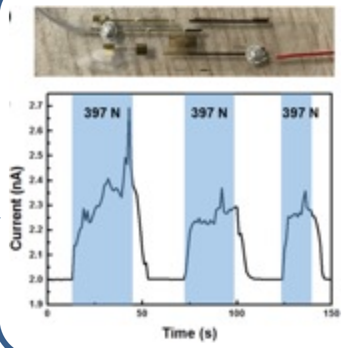
Density functional theory (DFT)



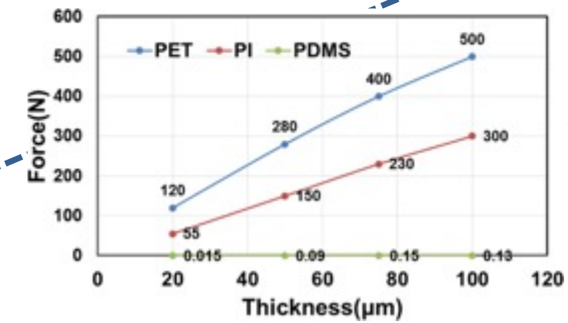
Stress distribution

Finite element anlaysis (FEA)

Benchmarking



Experiments



Optimizing the substrate of WS_2 stress sensor

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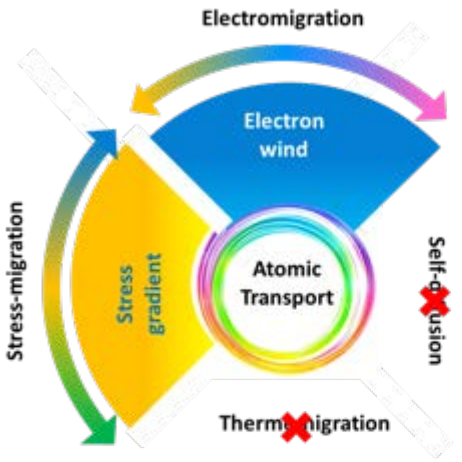
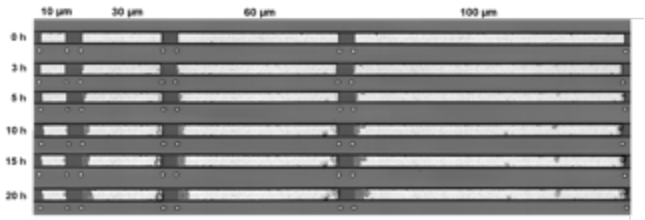
H Tang, D Hu, Z Cui, H Ye, G Zhang, ***The Journal of Physical Chemistry C*** 125 (4), 2680-2690, 2021

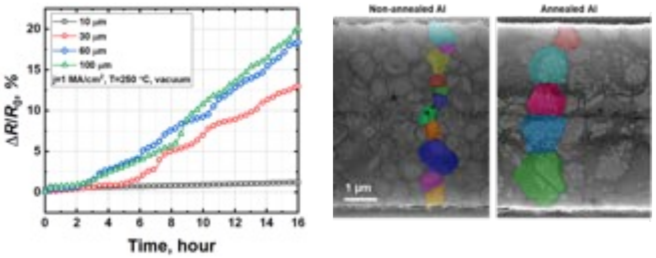
Material modeling and characterization: Electromigration

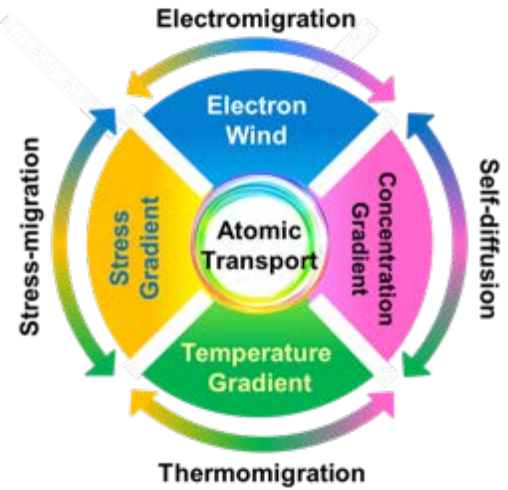


- Electromigration measurement



- Characterization

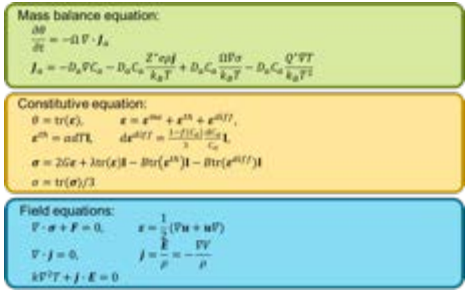


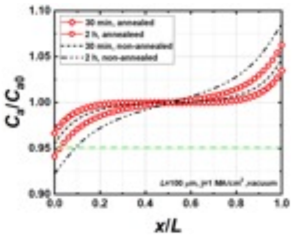


$$Z^* e\rho j + \Omega\frac{\partial\sigma}{\partial x} = 0$$

$$\boxed{jL = \frac{(\sigma_{max} - \sigma_{min})\Omega}{Z^* e\rho}}$$

Multi-Physics Fully-coupled Modeling





$$\left(1 + \frac{2EA\Omega f}{9(1-\nu)k_B T}\right)\frac{\partial^2 C_v}{\partial x^2} + \frac{Z^* e\rho j}{k_B T}\frac{\partial C_v}{\partial x} = 0$$

$$\frac{\partial^2 C_v}{\partial x^2} + \frac{Z^* e\rho j}{k_B T}\frac{\partial C_v}{\partial x} = 0$$

Cui Z. Fan X. J. Zhang G.Q. et al., **J. Appl. Phys.**, 2019

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Outlines

- Motivation
- State-of-Art
  - Material modeling and characterization
  - Process design and modeling
  - Tests and Qualifications
  - Health monitoring and lifetime prognostics
- Challenges and Roadmap
- Summary

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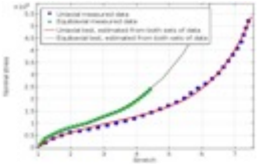
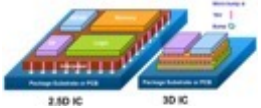
Physics of Failure (PoF) Based Reliability Modeling

Material Properties



Design Information



Application Conditions

Stochastic Process Modelling

Physics of Failure

Circuit-Field Model

Electronic Simulation
- Power distribution
- Critical output

Thermal Model

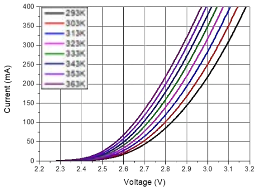
Thermal Simulation
- Temperature
- Model Parameters

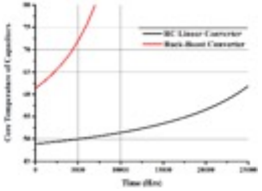
Failure or Degradation
- Temperature dependent
- Time dependent
- Model Parameter

Temperature/time dependent Failure or Degradation model

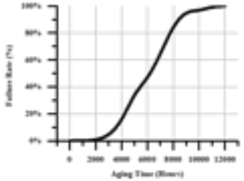
Monte Carlo Simulation

History of Electronic-Thermal Behavior

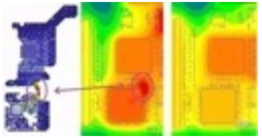




Reliability/ Lifetime/ MTTF

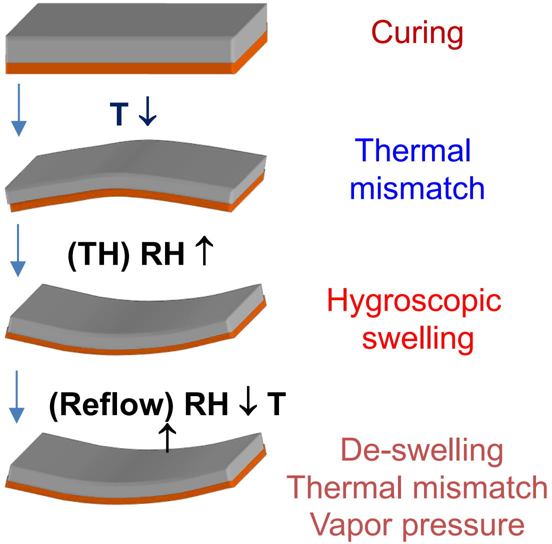


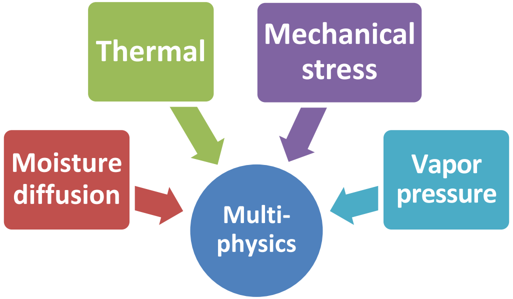
Critical Component & Material



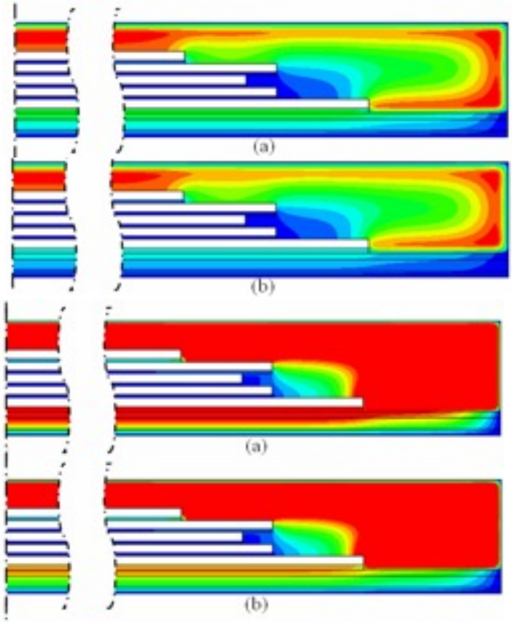
Process design and modeling: Reflow process

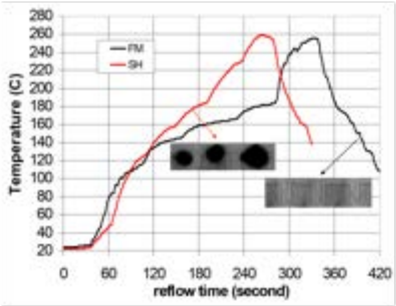
A Moisture-Thermal-Mechanical coupling modeling of moisture-induced stresses of IC packaging during reflow process





- **Moisture diffusion – water activity theory**
- **Vapor pressure theory**
- **Effective stress theory**





- Fan XJ, Moisture sensitivity of plastic packages of IC devices, Springer, 2010.
- Chen L et al., Microelectronics Reliability, Vol. 75, 2017, pp. 162-170.
- Chen L et al., Appl. Mech. Rev., 70(2), 2018, pp. 020803
- Ma L et al, 2019 IEEE 69th, 2019, pp. 806-810.
- Chen L et al., 2020 ECTC.

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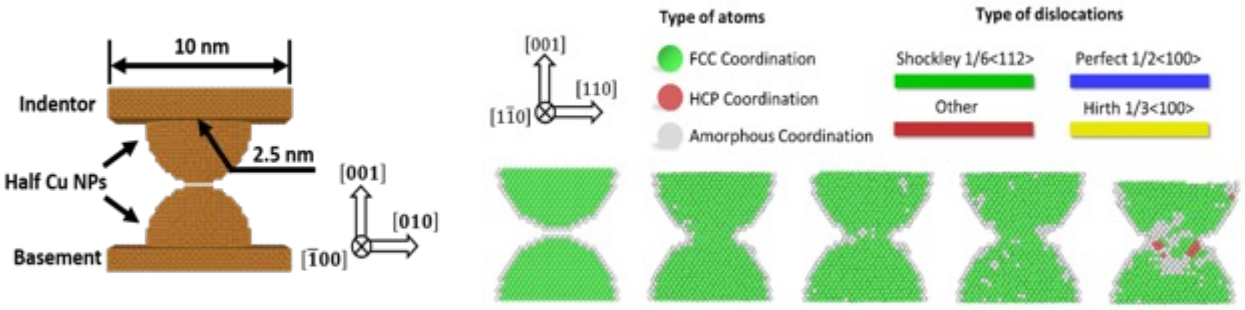
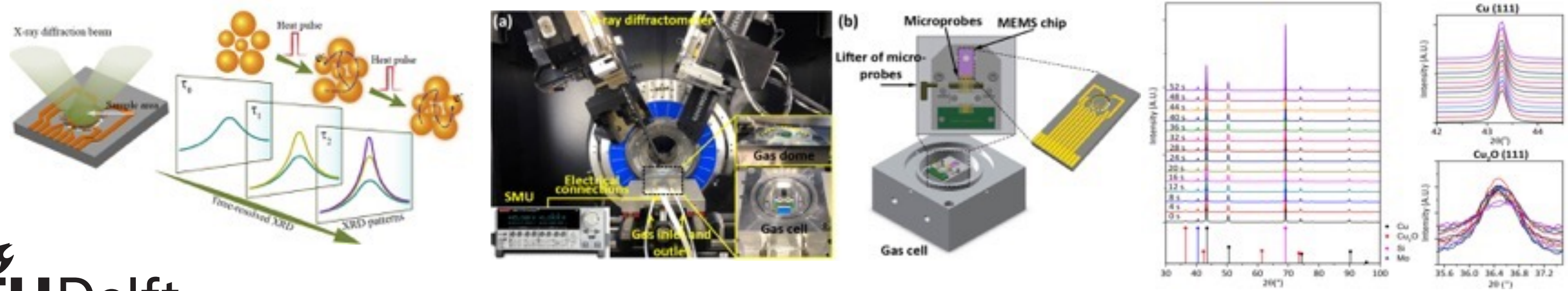
Process design and modeling: Sintering process

Molecular dynamics simulation: Pressure-assisted NanoCu sintering



Dong Hu, Zhen Cui G.Q. Zhang et al., **Results in Physics**, 2020

Process characterization: MEMS enabled time-resolved X-ray diffraction for NanoCu sintering



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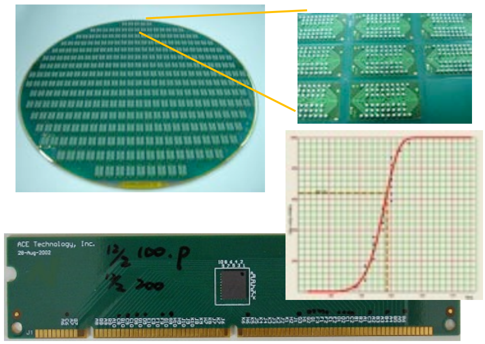
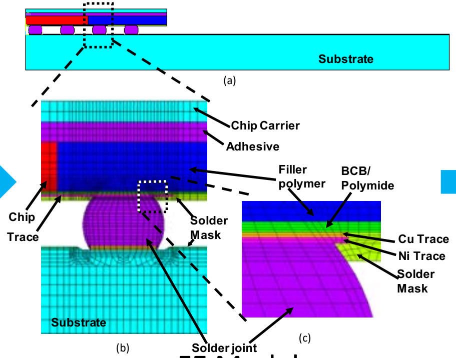
Boyao Zhang, PhD dissertation, **TU Delft**, 2020

Process design and modeling: FC packaging process

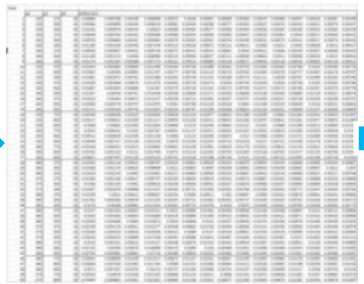
AI assisted highly reliable Flip chip packaging design



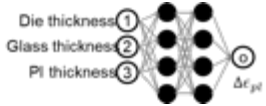
Lifetime Experiment



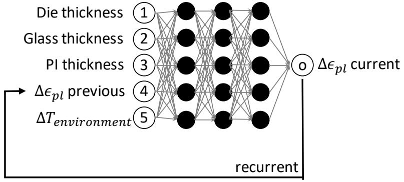
FE Model



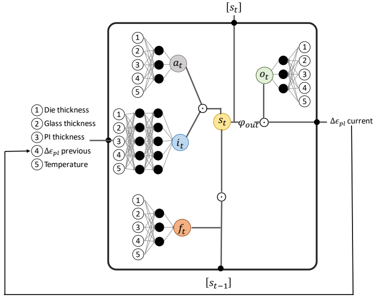
FE-datasets



ANN

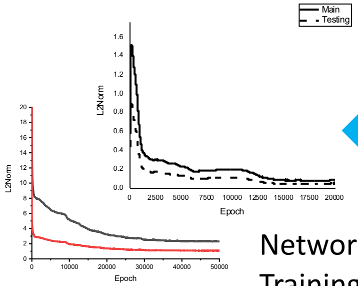


RNN

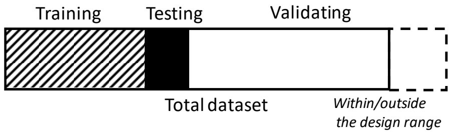


LSTM

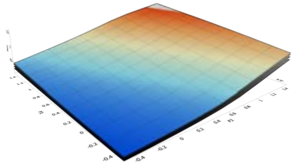
Network Selection



Network Training



Validation



Optimization

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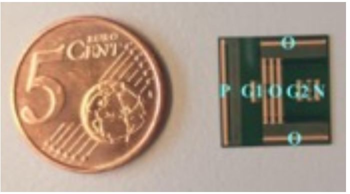
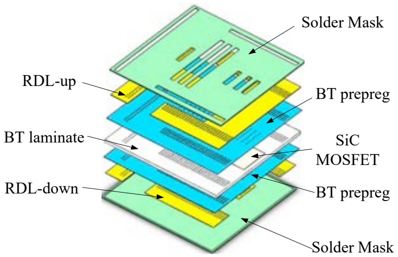
Yuan C and Lee C.C., 2020 21th EuroSimE
Yuan C et al, 2019, 20th EuroSimE

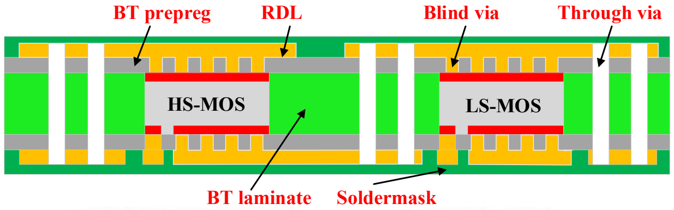
Liu W et al, 2020 70th ECTC
Chou P et al, 2019 69th ECTC

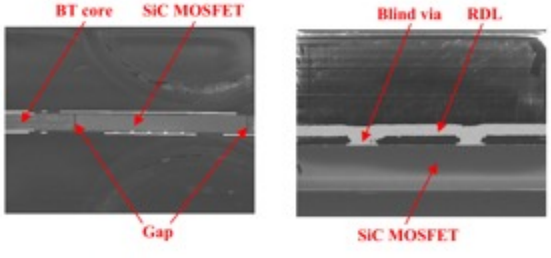
Process design and modeling: SiC MOSFET module

Fan-Out Panel-Level SiC MOSFET Power Module





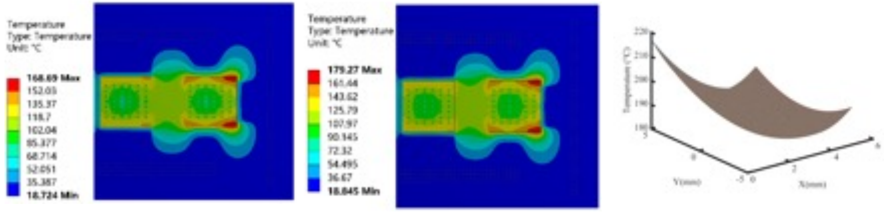




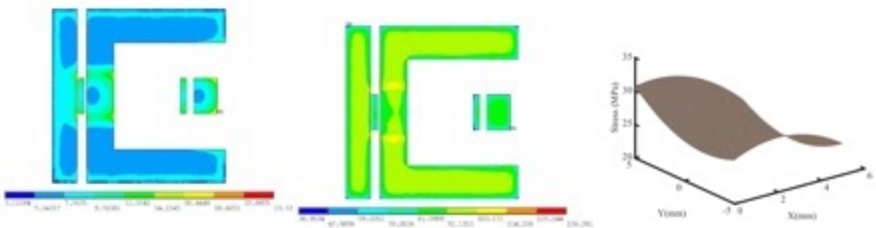
(a) HS-MOS region

(b) Local zoom-in

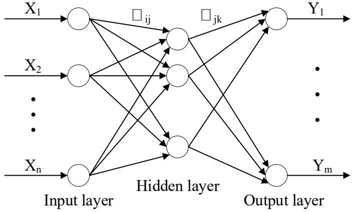
Ant Colony Optimization-Back Propagation Neural Network



Thermal optimization



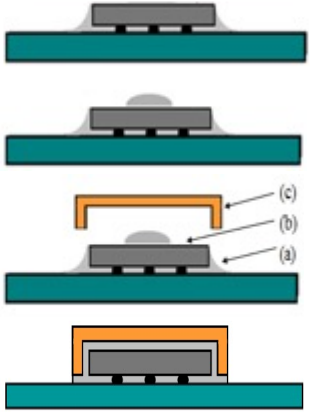
Thermal-Stress optimization



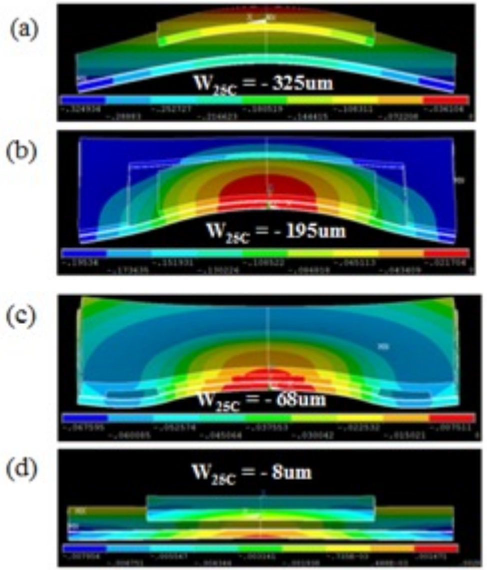
	After RSM	After ACO-BPNN	Before optimization	Percentage improvement by RSM	Percentage improvement by ACO-BPNN
Temperature T (°C)	180.71	180.40	187.02	3.38%	3.50%
Stress σ (MPa)	24.453	24.728	27.490	11.05%	10.04%

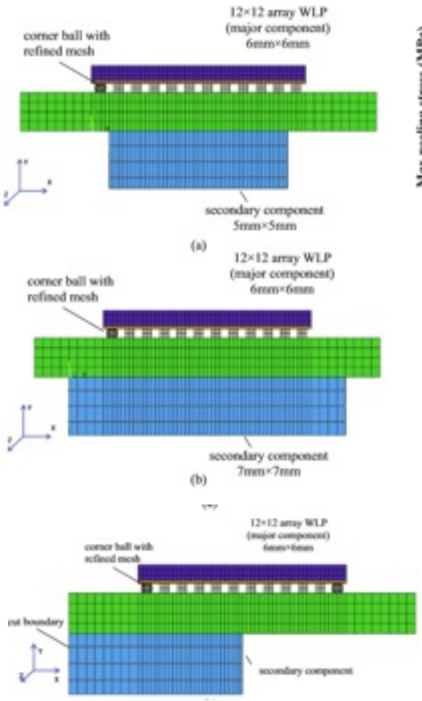
Y. Qian, F. Hou, J. Fan, Q. Lv, X. Fan and G. Zhang, *IEEE Transactions on Electron Devices*, doi: 10.1109/TED.2021.3077209.

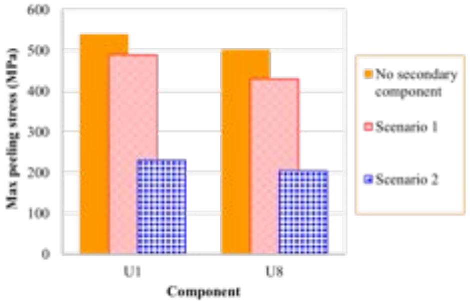
Process design and modeling: Chip/Package/System Co-Design

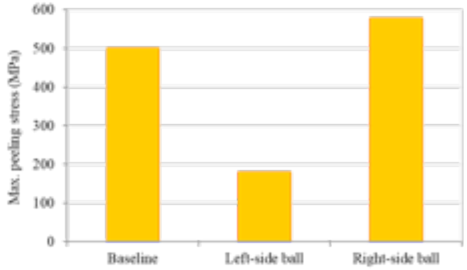


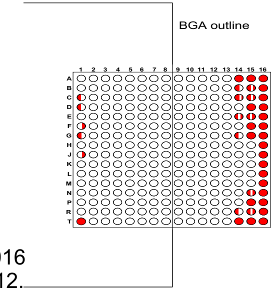
Capped-Die Flip Chip Package











- Warpage-free packaging with a capped-die flip chip package co-design (cap/board thickness, underfill property…).
- WLP placement/secondary component at system level.

Shen Y et al., IEEE Transactions on CPMT 6(9), 1308 – 1316. 2016
Fan XJ et al., IEEE Transactions on CPMT. 2(11), 1802-1810, 2012.

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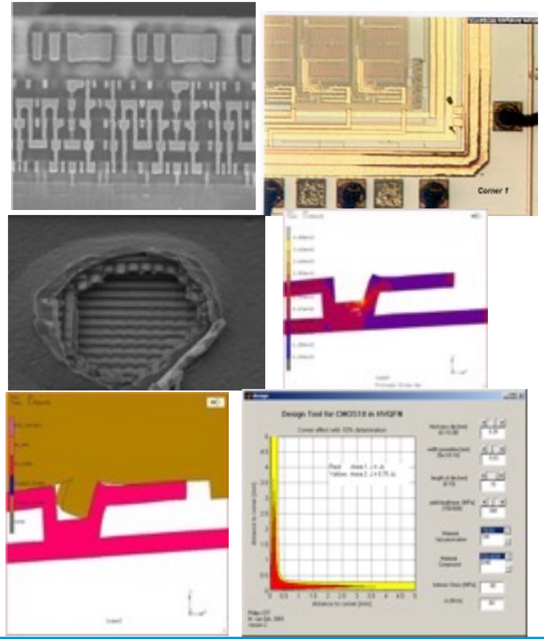
Example: CMOS 90/65nm IC/packaging co-design

Problem & Challenges

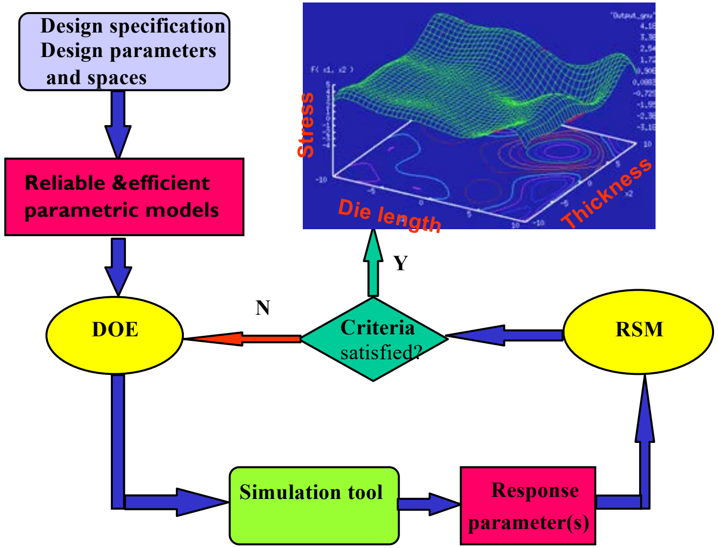
Multi-physics; multi-failure mode;
non-linear & time dependent;
simulation-based optimization



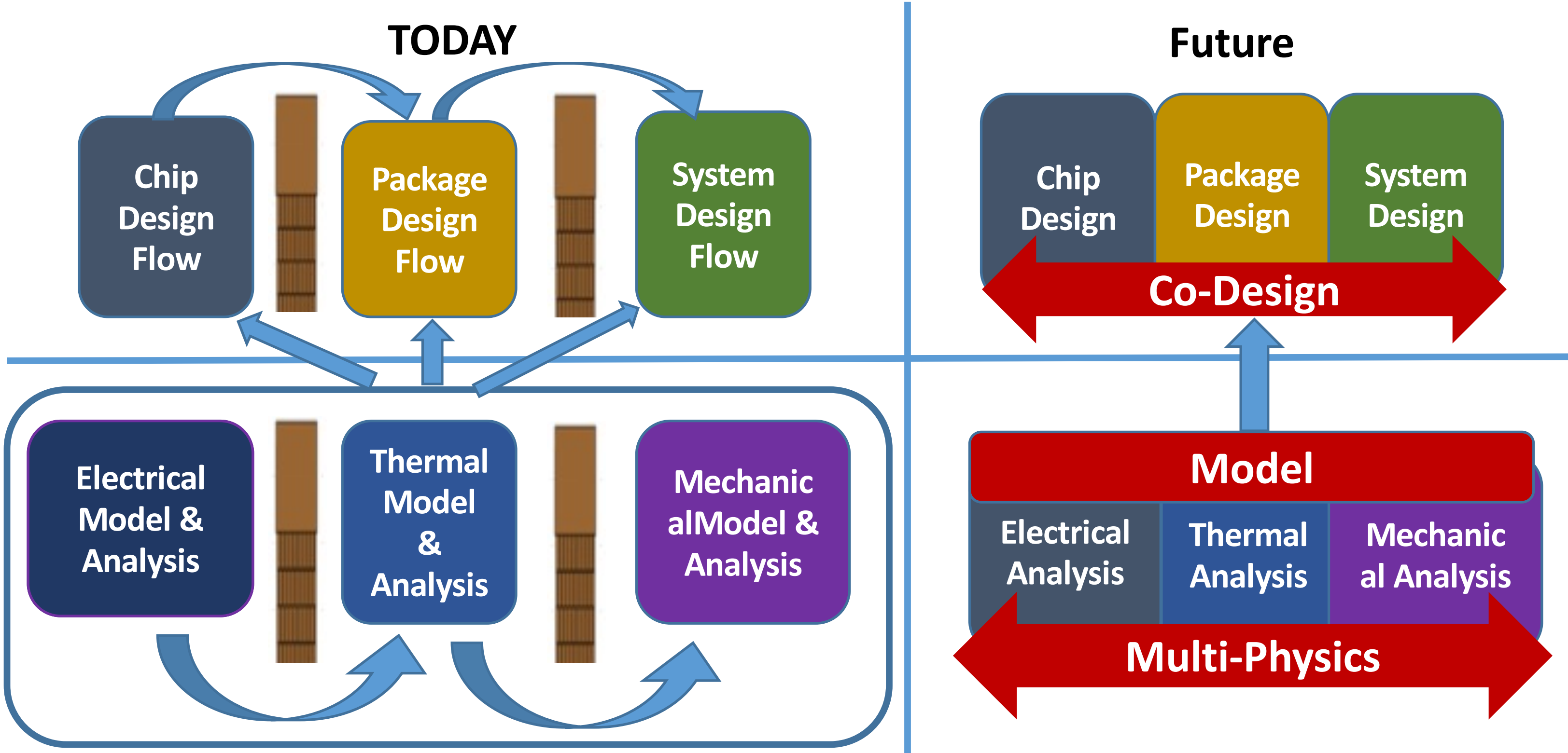
Objective

Develop IC/package co-design tool that can ensure the thermo-mechanical reliability, as the functions of waferfab backend process and packaging design parameters

Methods



Moving towards a new paradigm



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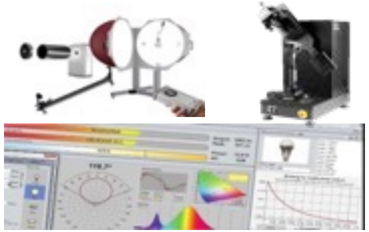
Tests and Qualifications

Functional Performance Test

Optical | Electrical
Functions and Performances
RF | …

Optical Performance Tests



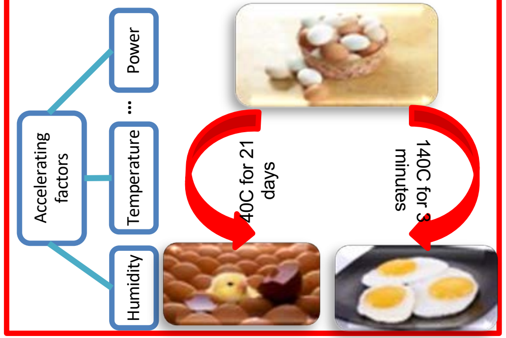
Electrical Performance Tests

IGBT Test Equipment from DYNEX

…

Accelerated Reliability Qualification and Test

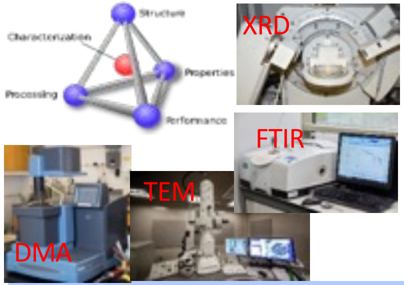
Testing strategy



Test Platforms and Methods

Basic Test

Material Characterization



Thermal Tests

Thermal resistance and Junction temperature testing

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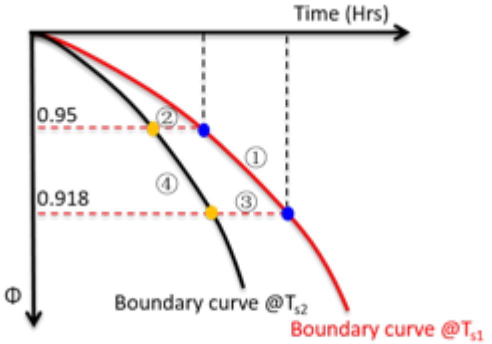
Goals:

- Cost effective testing strategy and test methodologies;
- Automated test pattern generation, data analysis and diagnosis flows;
- Multifunctional performance testing;
- Multi-scale testing;
- Multi domain cross talk;
- Complex system testing.

Tests and Qualifications

Accelerated Test Method of Luminous Flux Depreciation for LED Luminaires and Lamps

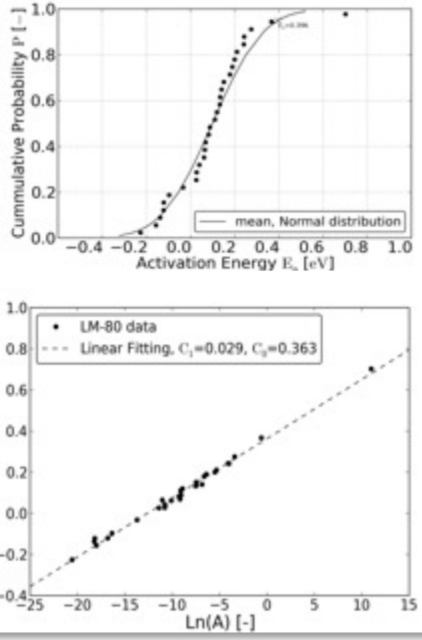
Two-stage accelerated model



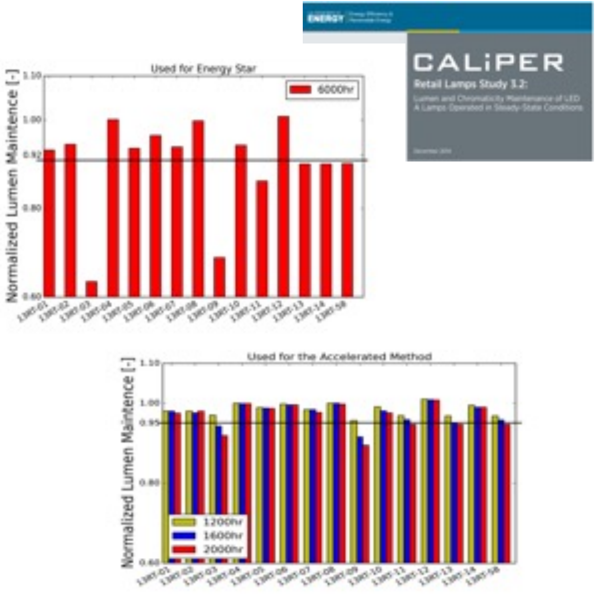
$$AF = \frac{\alpha|_{Ts1}}{\alpha|_{Ts2}} = e^{-\frac{E_a}{k}\left(\frac{1}{T_{s2}}-\frac{1}{T_{s1}}\right)}$$

$$L_{95}|_{Ts2} = \frac{L_{95}|_{Ts1}}{AF}$$

Parameters determination



Model validation



Reliability Engineering & System Safety, Volume 147, 2016

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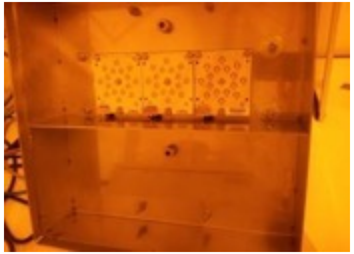
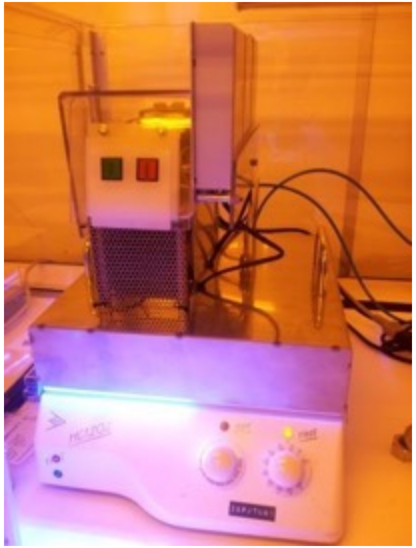
An accelerated test method for luminous flux depreciation to reduce the test time from 6000 to 2000 hours at an elevated temperature

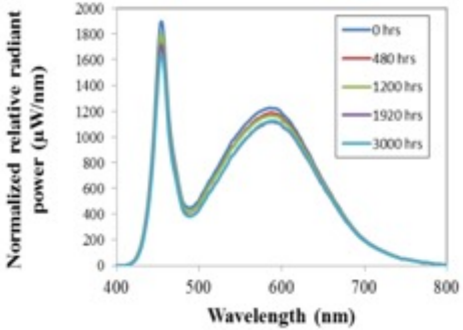
Tests and Qualifications

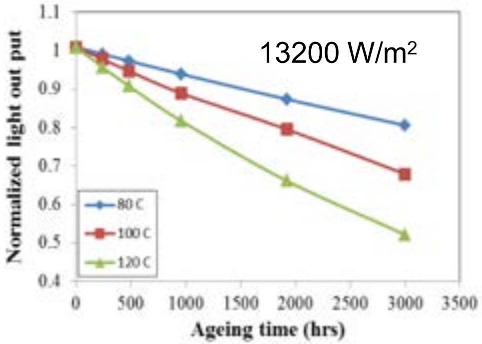
Accelerated Tests of Remote Phosphor: PC+ YAG:Ce

- Remote phosphor: PC+ YAG:Ce
- Ageing at 80, 100, and 120 ºC for 3000 h
- Light intensity of: 825, 3300,13200 W/m^2







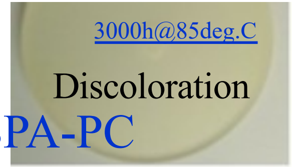


Light intensity (W/m2) / Temperature (°C)	**825**	**3300**	**13200**
80	4410	4370	4300
100	4120	4000	3900
120	4050	3900	3720

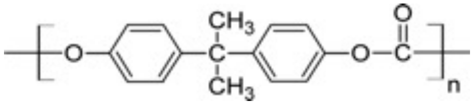
Maryam Yazdan Mehr; van Driel, WD; GuoQi Zhang; ***Microelectronics Reliability****, Volume 54, Issue 8, pp. 1544-1548, 2014.*

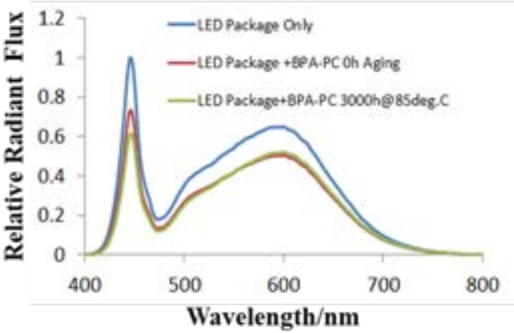
Tests and Qualifications

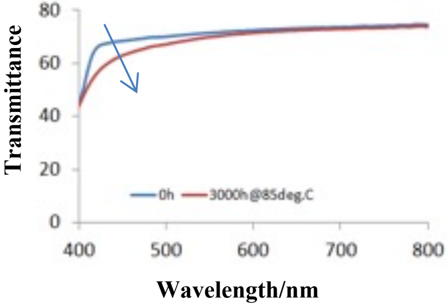
Color Shift-high temperature accelerated ageing tests of LED diffuser/Lens

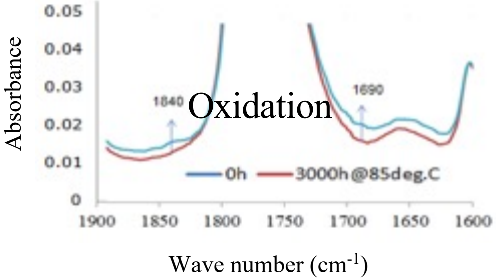


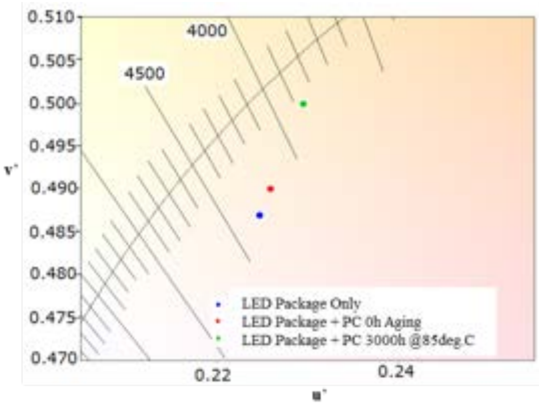
Diffuser-BPA-PC











Inconsistent degradation of wavelength–dependent transmittance

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Lu GJ, Mehr MY, van Driel WD, Fan XJ, Fan JJ, Jansen KMB, and Zhang GQ, *Optical Materials*. vol. 45, pp. 37–41, 2015.

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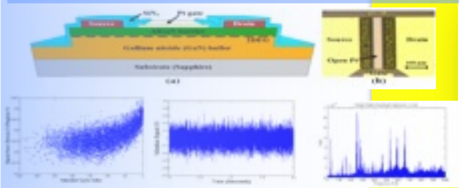
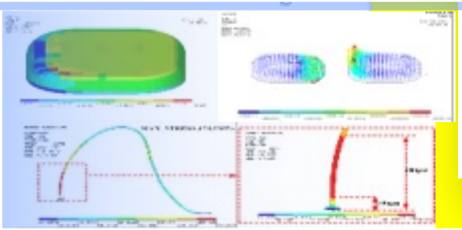
Health monitoring and lifetime prognostics

Monitoring with advanced sensors

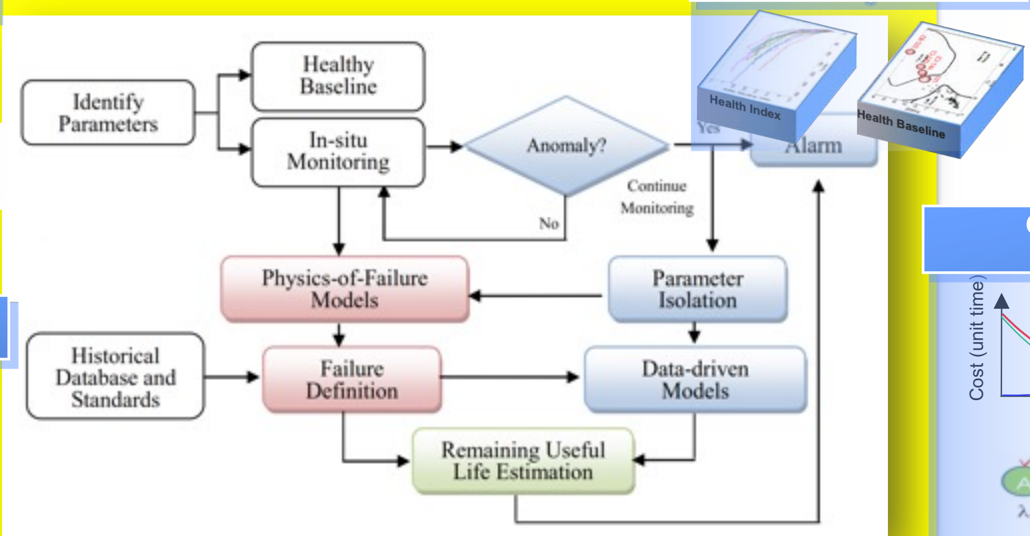


Temperature, Vibration, Pressure etc.

Multiscale/Multiphysics-of-Failure modelling



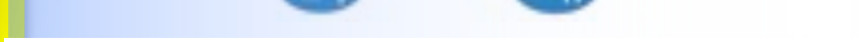
Possible solutions:
First principle, Molecular Dynamics, FE Simulation etc.



Machine learning based fault diagnostics

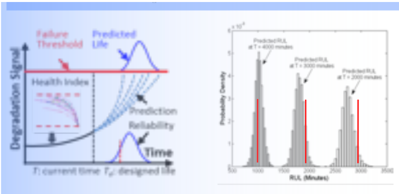
Possible solutions:
Support vector machine, k-nearest neighbors, Principal components analysis, etc.

Condition Based Maintenance



Possible solutions:
Bayes' Theorem, Hidden Markov model, etc.

Data-driven based RUL prediction



Possible solutions:
Stochastic regression, Nonlinear Filtering, artificial neural network etc.

Prognostics and Health Management of Electronics: Fundamentals, Machine Learning, and the Internet of Things, **2018 John Wiley and Sons Ltd**

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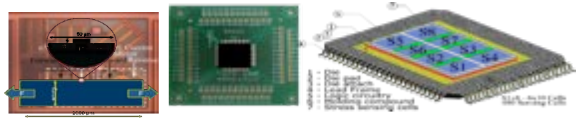
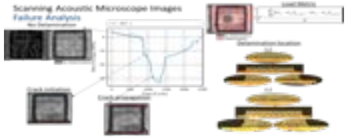
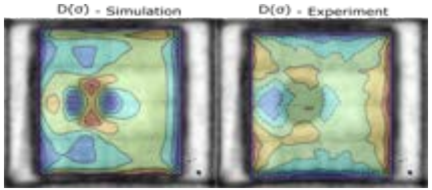
Health monitoring and Lifetime Prognostics: Fusion method

iForce – piezoresistive stress sensor







FMMEA
Physics of Failure
Data driven approach

Failure modes

Infrastructure
Sensors
Hardware

Sensing the signal

Modeling
Model order reduction
Metamodels

Damage evaluation

Diagnostics, Prognostics and Health Management for Power Electronics

Data management and transfer

Car to X communication

Data acquisition

In-situ data evaluation

Health Index

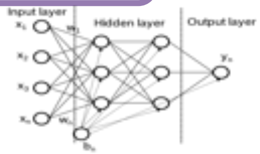
Detecting anomalies

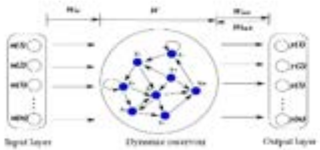
RUL calculation

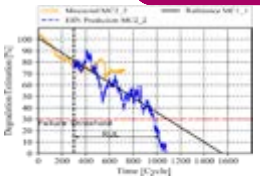
Health assessment

Diagnostics

Prognostics



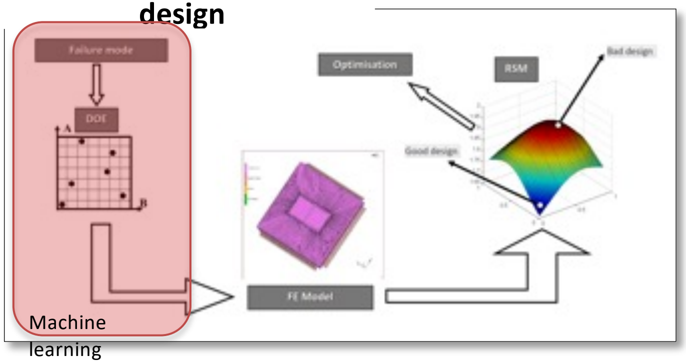




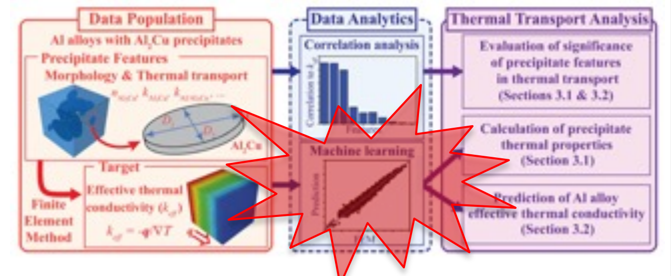
A Prisacaru, PhD dissertation, **TU Delft**, 2021

AI assisted Simulation & Design

AI assisted optimal design

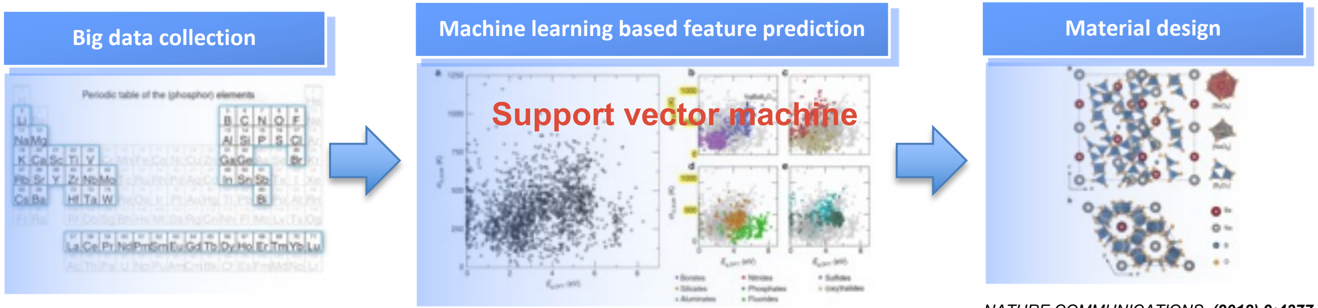


AI assisted FEA simulation



Adv. Theory Simul. ***2019*, *1800196***

AI assisted new material design



NATURE COMMUNICATIONS **(2018) 9:4377**

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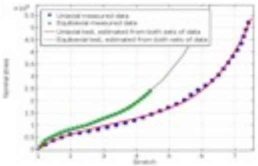
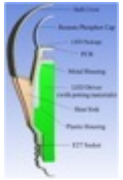
Lifetime Prognostics: PoF method for LEDs

Material Properties



Design Information



Application Conditions

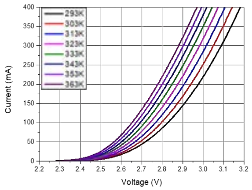
Stochastic Process Modelling

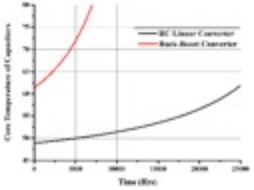
Physics of Failure

- **Electronic Simulation**
- **Optical Simulation**
- **Thermal Simulation**
- **Failure or Degradation**
  Temperature/time dependent Failure or Degradation

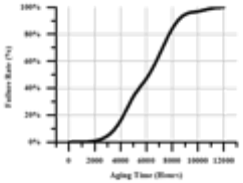
Monte Carlo Simulation

History of Electronic-Thermal Behavior

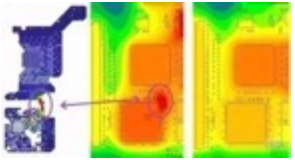




Reliability/ Lifetime/ MTTF



Critical Component & Material



B. Sun, X.J. Fan, G.Q. Zhang et al., **RELIABILITY ENGINEERING & SYSTEM**, 2017;
B. Sun, X.J. Fan , G.Q. Zhang et al., **IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS**, 2016

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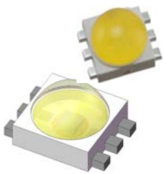
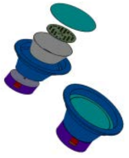
Lifetime Prognostics: Data-driven method for LEDs



Accelerated degradation test to collect lumen maintenance data

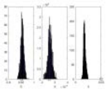


↓

Identify physical model describing LED degradation

↓

Model parameter estimation using MCMC (Metropolis Hasting)



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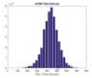
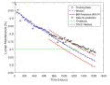
Projecting long-term lumen maintenance based on Physical model and predicted parameters

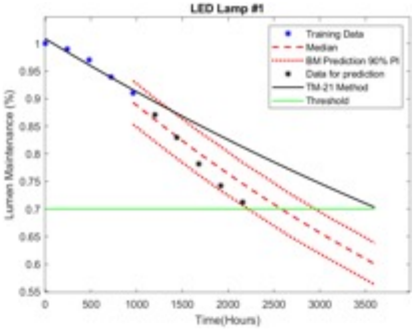
↓

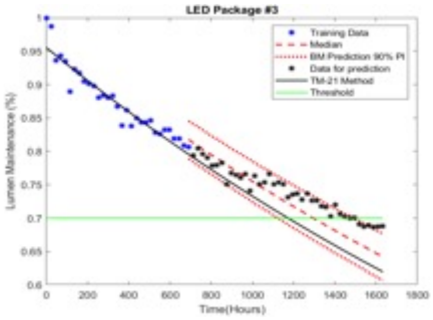


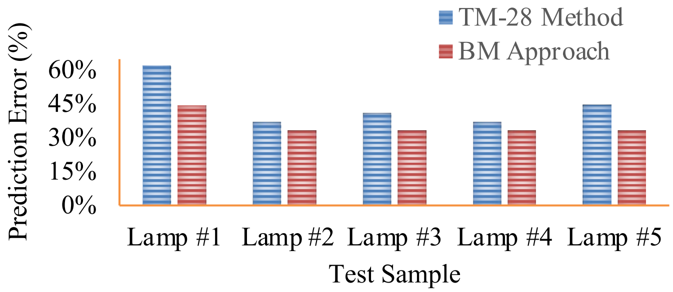
Remaining Useful life Prediction based on failure threshold

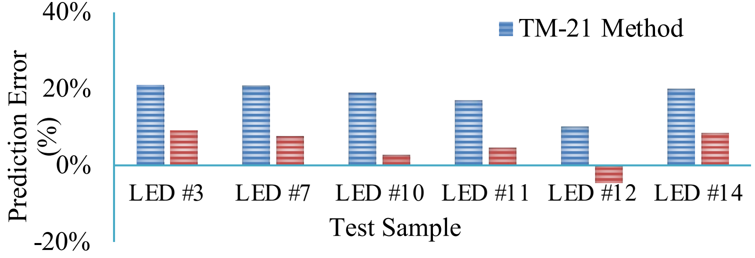


Bayesian method (BM)









- The exponential decay model is used as the degradation model and the parameters are estimated based on **Markov Chain Monte Carlo (MCMC) sampling** and using **the Metropolis-Hasting (MH) algorithm**.
- The lifetime prediction results showed that **the Bayesian method has better prediction accuracy compared to the NLS method.**

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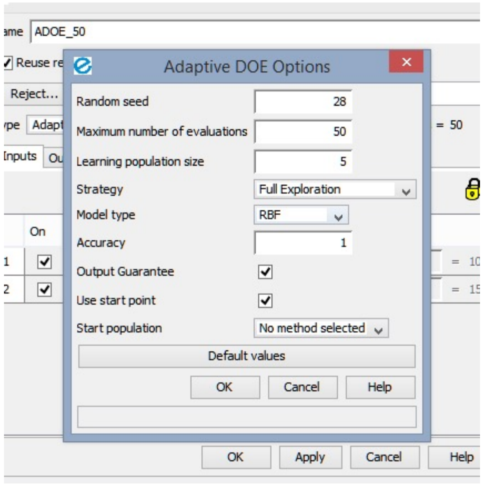
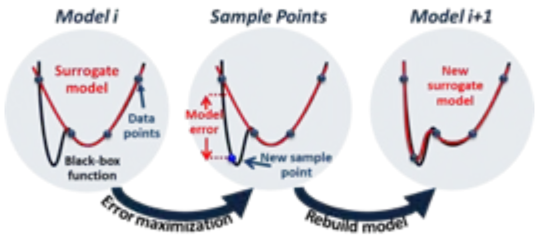
MS Ibrahim, Z Jing, WKC Yung, J Fan, **Expert Systems with Applications** 185, 115627, 2021

Metamodel based AI using Adaptive DOE

- A **machine learning technique** that aims to provide the best metamodel fitting capability given a certain design space.
- An **iterative approach** that learn and focus on the most interesting regions for the creation of a better metamodel.
- A flexible methodology that smoothly scales from single output to **multi-output problems**
- A powerful technique that avoids **undersampling** and/or **oversampling** issues.





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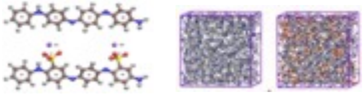
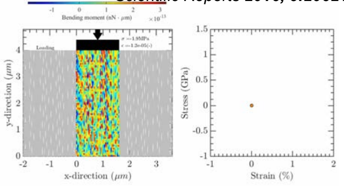
Multiscale & Multiphysics modeling

Atomic and molecular scales

First-principles &Molecular Dynamics



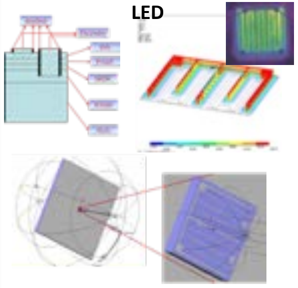
Scientific Reports **2016, 6:20621**



Adv. Funct. Mater. **2016**

Chip level (Micro scale)

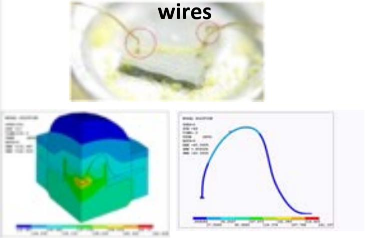
Electro-optical simulation of LED



MR, **2017, 74:173-178**

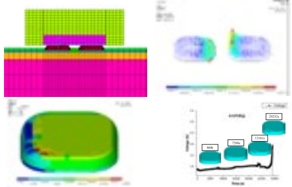
Package and module levels (Centimeter scale)

Fatigue simulation of bonding wires



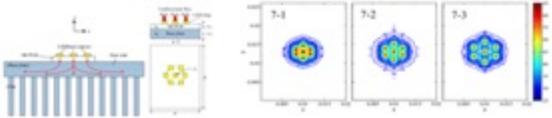
ICEPT **2017:1-5**

Electromigration simulation



ICEPT **2017:1133-1137**

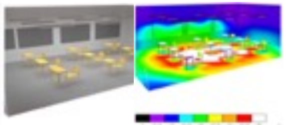
Thermal simulation of multiple LED chips



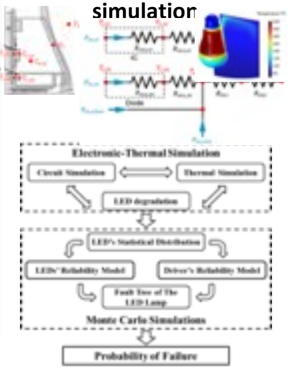
IEEE ACCESS. **2017, 5:16459-16468**

System level (meter scale)

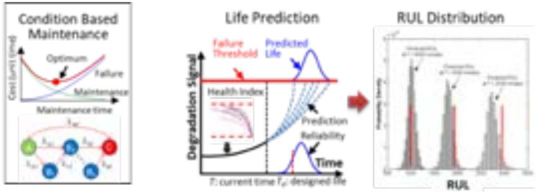
Spatial lighting simulation



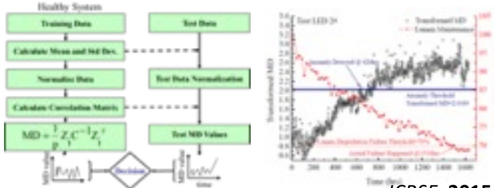
System reliability simulation



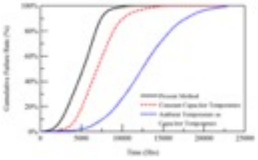
System prognostics & maintenances



System diagnostics



ICRSE, **2015, 1-6**



RESS, **2017, 163: .14-21**

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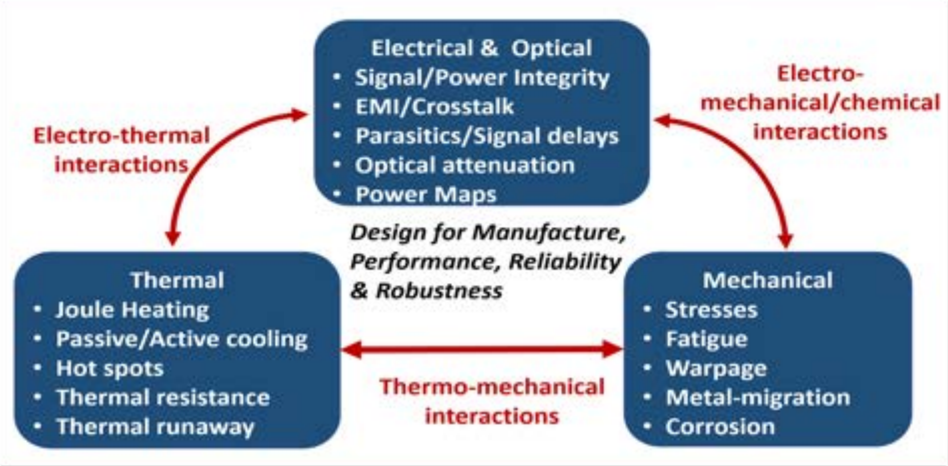
Scale: Devices (nm) Packages(um-mm) Boards (mm-cm) Systems (cm-m)

Data:
Materials
Manufacturing
Characterization;
Mission Profiles,
Industry 4.0, etc



Knowledge Base:
Design Rules,
PDK's ADK's, etc

Model Fidelity: Analytical Circuit/Network Compact/Response Surface MOR MD/FEA/CFD

Model based Optimization; Big Data Analytics; Physics of Failure Models; Prognostics; etc.

Question:

“We developed a new product/system, by using new materials and new technology, can you tell when will it fail and how? “

My answer is NO.

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- In principle, all simulation results are wrong, unless you can prove they are right
- Experiments (characterization and verification) will remain as the key success factor for simulations and modeling
- Easier to develop sophisticated simulation models, than to build a simple ones
- It is easier to make ones' models beautiful than useful. But, nice pictures will not make your boss happy. The ultimate aim is to achieve ”Design on Demand” - SOLUTIONS
- Key mission of simulation community: to liberate the simulation experts by combined data, physics of failure based models with AI/ML.

Outlines

- Motivation
- State-of-Art
  - Material modeling and characterization
  - Process design and modeling
  - Tests and Qualifications
  - Health monitoring and lifetime prognostics
- Challenge and roadmap
- Summary

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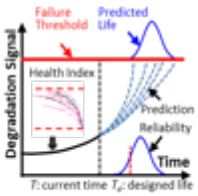
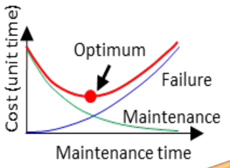
Physical twin challenges:

- Rapid prototype
- First-time-right design
- Optimized performance & designed in reliability
- Low cost and reliable sensing and in-situ monitoring
- Self healing
- Remaining useful life prediction
- Proactive maintenance
- C2C and lifecycle optimization





Current

- Rapid prototype
- First-time-right design
- Optimized performance

3-5 yrs

- Sensing and in-situ monitoring
- Accurate fault alarm
- Remaining useful life

5-10 yrs

- DT chip/function integrated
- Performance and lifetime on demand
- D4X

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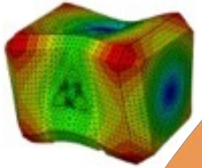
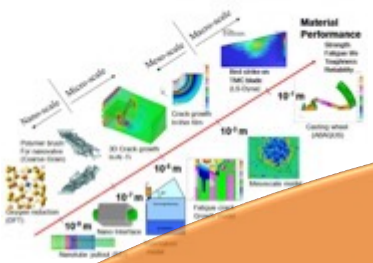
Digital twin challenges:

- Accurate and efficient simulation models
- Nonlinear, time and temp dependent
- Fast and accurate multi-scale/multi-physics/full-process simulations
- From deterministic to probabilistic/stochastic simulation
- Accurate failure threshold definition
- Multi-failure modes interaction & solution
- Automated model generation and simulation
- Compact models
- Integration of physics of failure based models with ML and data driving models
- Simulation based optimization/design& operating rule
- …





Current
- Analytical/empirical models
- 1st principle/MD quantitative
- FEA modeling for known failure modes
- Trial-and-Error

3-5 yrs
- Integrated multiscale/multiphysics simulations
- Optimisation & design rules
- AI assisted & data driven simulation and design
- Design for reliability

5-10 yrs
- Multi-scale/multi-physics/full-process simulations
- Nonlinear, dynamic, probabilistic /stochastic simulation
- AI/data driven automated simulation models
- Design 4 X
- Upgradeability

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Connectivity challenges:

- Cloud platform and connection
- Low cost and reliable real-time monitoring
- Big data storage, transmission, smart filtering, computing, close loop control algorithm
- Smart sensing and IoT wireless communication
- Highly reliable embedded DT chip/MCU integration
- …

Current

- Weak connection
- No closed loop
- Limited data of in-situ monitoring

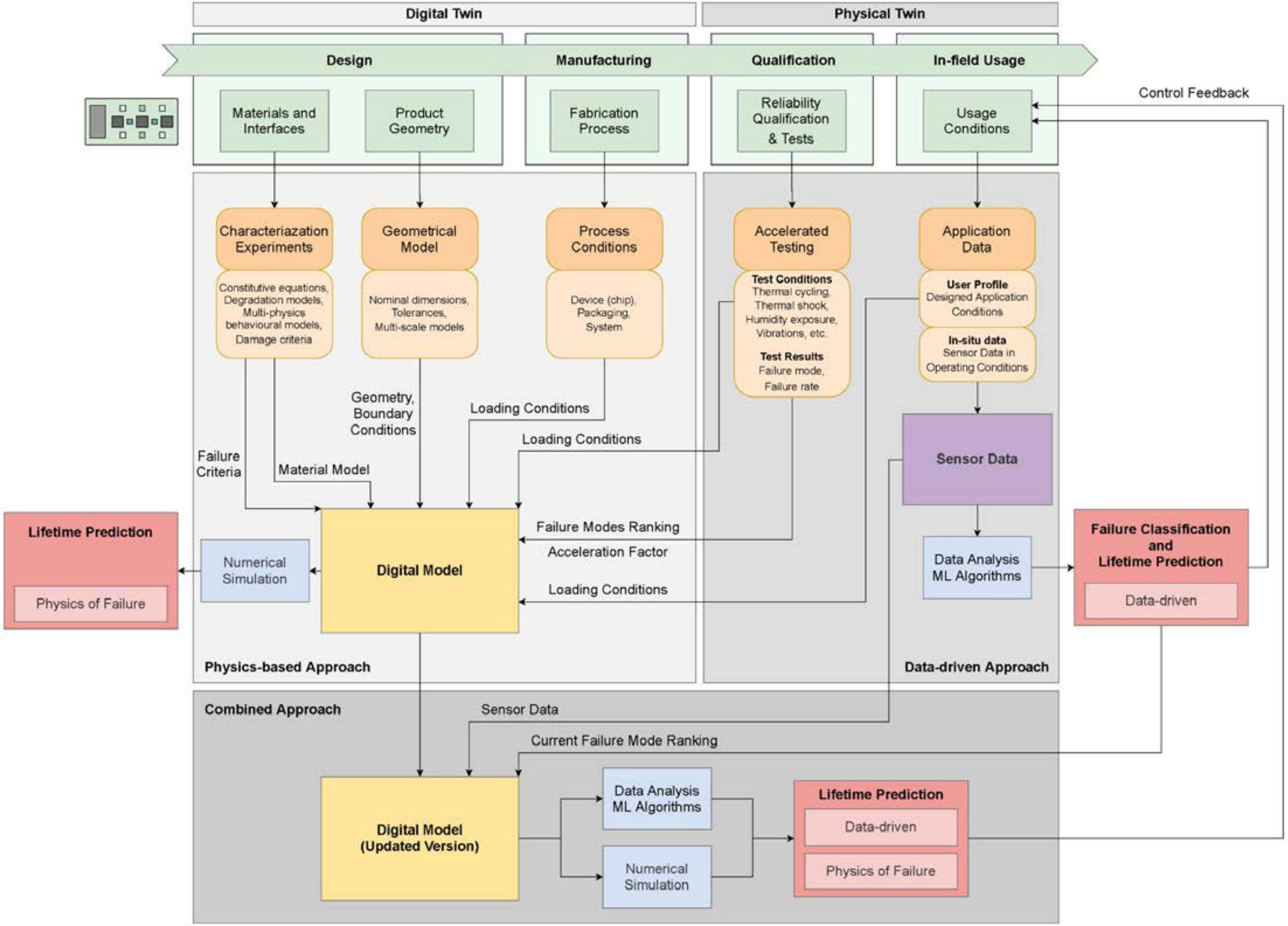
3-5 yrs

- Cloud platform
- Real-time key parameter monitoring
- Big data storage, filtering, transmission and computing
- IoT wireless communication
- Separated closed loop

5-10 yrs

- Smart in-situ sensing and transmission
- Edge computing
- Highly reliable embedded DT chip/integrated with MCU

Lifetime Prediction Digital Twin System : Structure of Data Flow and Processing



Outlines

- Motivation
- State-of-Art
  - Material modeling and characterization
  - Process design and modeling
  - Tests and Qualifications
  - Health monitoring and lifetime prognostics
- Challenges and roadmap
- Summary

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Summary

- Driven by the ever-increasing societal needs for digitalization and intelligence, such as autonomous driving, Manufacture 4.0, “Smart-X”, “AI in all”, the demands for mission critical electronics components and systems are growing fast.

- To realize “performance and lifetime on demand” for mission critical electronics, DT will play an essential role.

- The DT must be able to represent the PT reliably and efficiently, to achieve the ultimate aim of 1+1>2.

Summary

- From analytical, empirical and numerical to NOVEL methods, evolutionary / revolutionary modeling& simulation ideas are not mature yet.

- Integrated & concurrent development of physics of failure based models with AI driven big data/ML are possible solutions to predict the multi-scale/multi-physics/full process/nonlinear/stochastic/time and temperature dependent responses of mission critical electronics.

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Thanks for your attention