Data-driven Modelling for Power Module Condition Monitoring

TWIND Online Summer School

08/July/2021 | Chunjiang Jia (CJ)

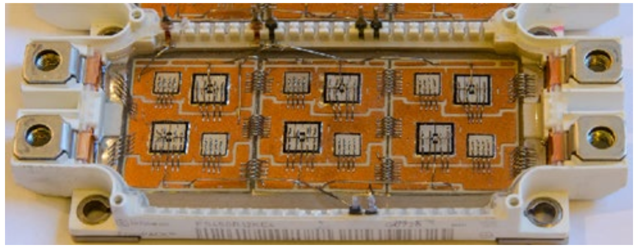
CATAPULT Offshore Renewable Energy

Agenda

- Power module failure mechanism
- Heat flux detection method
- Artificial neural network
- ANN-based heat flux detection
- Test and verification
- Summary

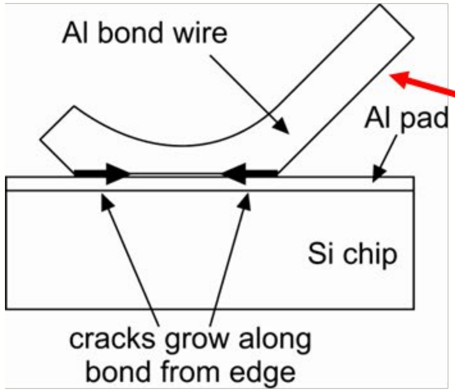
Power Module Failure Mechanism

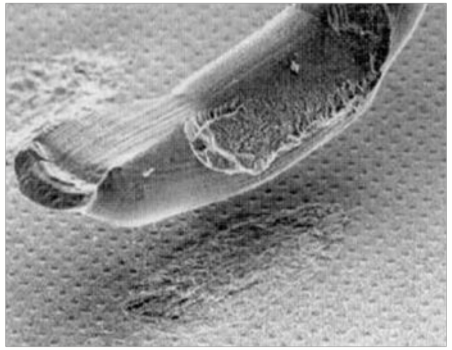
Col. A



Col. B

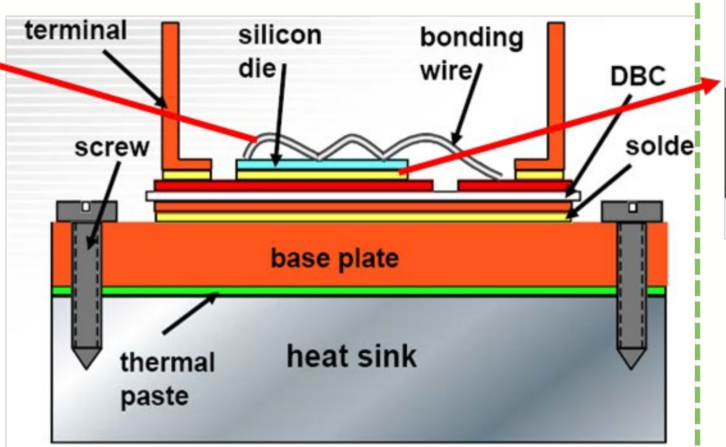
Bond wire lift-off





Col. C

Thermo-mechanical stress accumulation

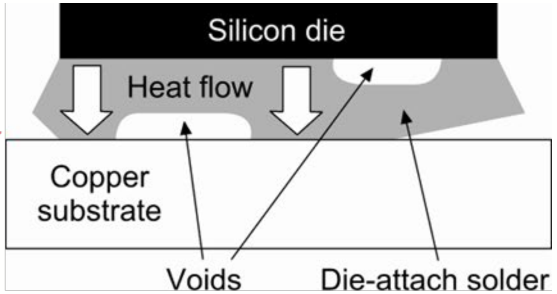


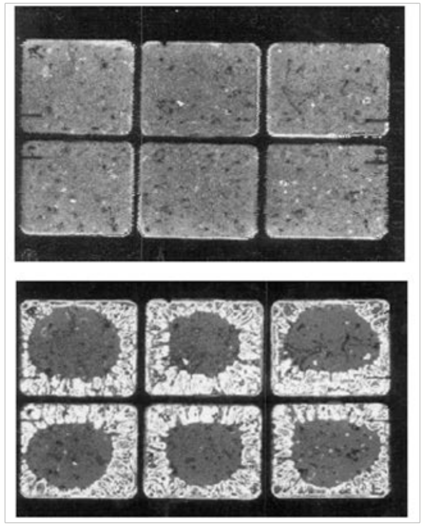
Coefficient of Thermal Expansion (CTE)	
silicon	$4.1*10^{-6}K^{-1}$
DBC - Al2O3	$7.4*10^{-6}K^{-1}$
copper	$17.5*10^{-6}K^{-1}$

Solder SAC305 $23x10^{-6}K^{-1}$

Col. D

Solder delamination





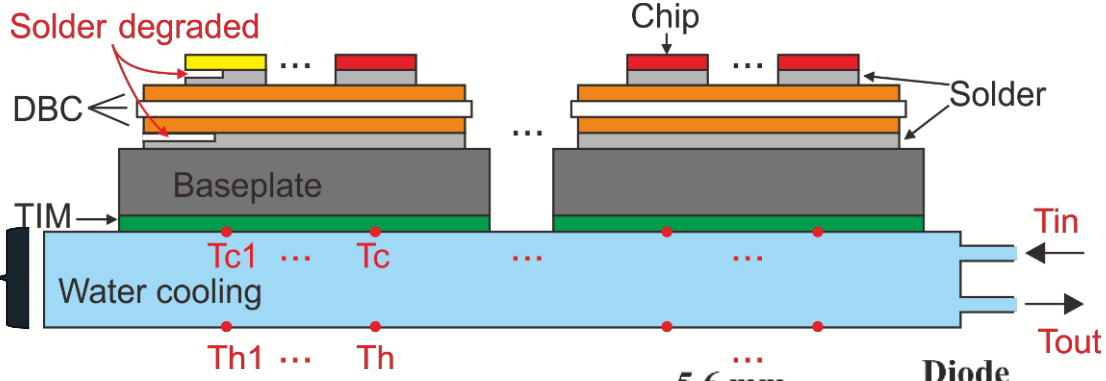
Detection methods:

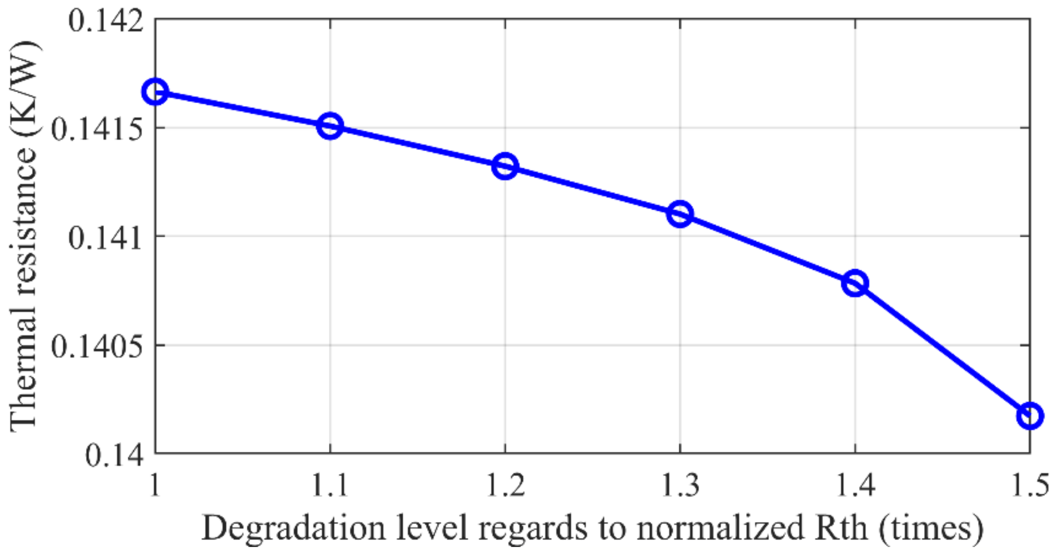
- TSEP, thermal sensitive electrical parameter to monitor the degradation
- Heat flux, the degradation causes the Rth of thermal path to increase, which will influence the heat transfer rate through the layers

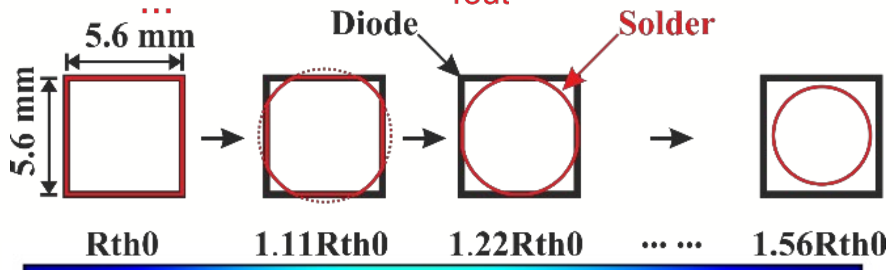
Thermal FEA Simulation

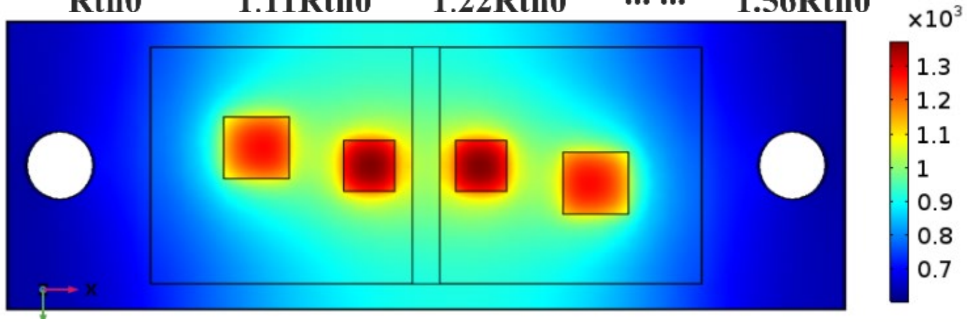
Heatsink Thermal Resistance:

R_{th} *= (Tc-Th)/power loss*







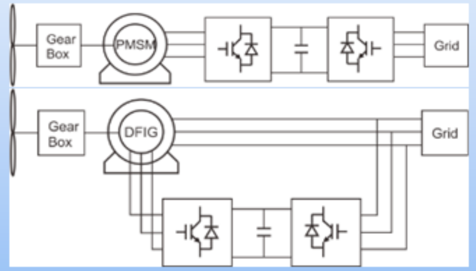


- When the degradation happens to the solder, the temperature drop is becoming larger from chip to heatsink, causing Rth decreasing
- The mapping between the temperature distribution (thermal) and the operating point (electric) can be used to indicate the level of solder degradation

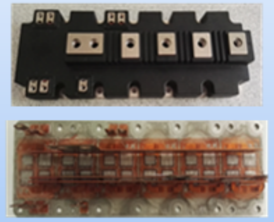
Thermal Resistance: R_{th}= ΔT/power loss

- ❑ Electric performances (power loss related) of power modules are temperature dependent
  - An electric and thermal coupled result
- ❑ Degradation is a non-linear and multiphysics process for multi-chip power modules
  - A complex thermal network model with multiple-input and multiple-out (MIMO)
  - A large number of look-up tables required
- ❑ Therefore, it is challenge to develop a model-based analytical method to implement heat flux condition monitoring online for multi-chip power modules

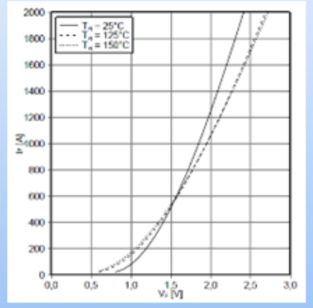
Electro-thermal modelling



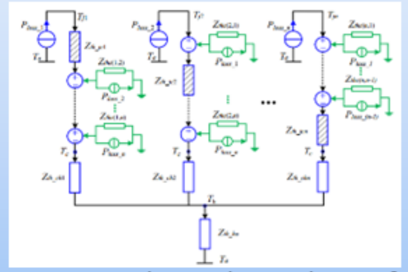
Uneven degradation



Multi-chip in MW module



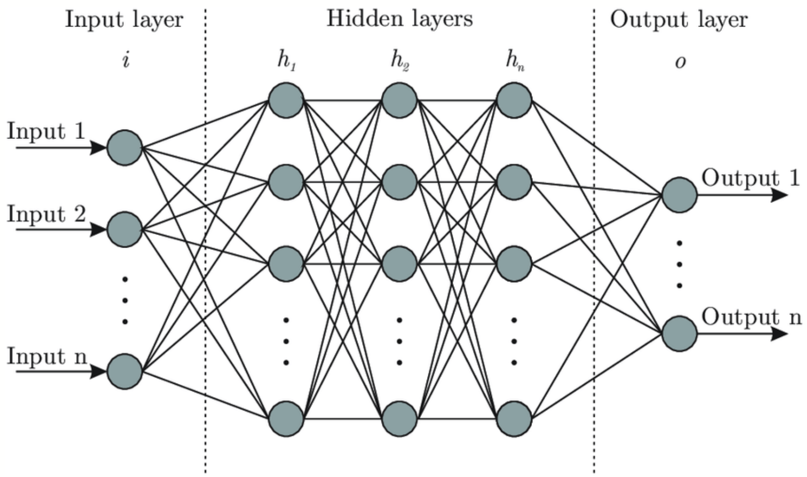
Coupling analysis



-Current sharing
-Power losses
-Thermal runaway

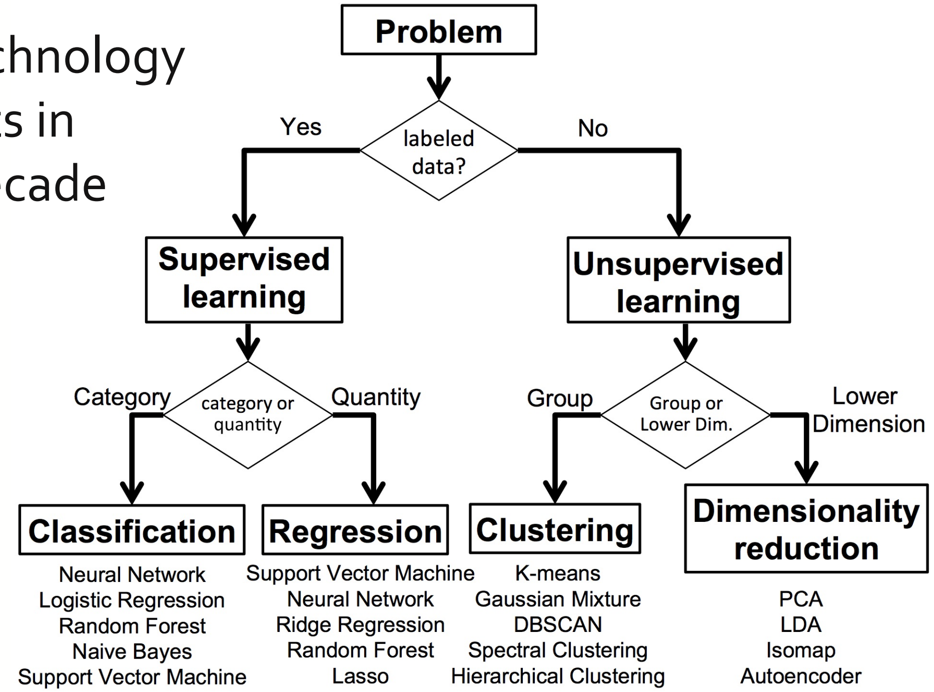
The on-line solution for thermal-mechanical performance is complex.

Artificial Neural Network

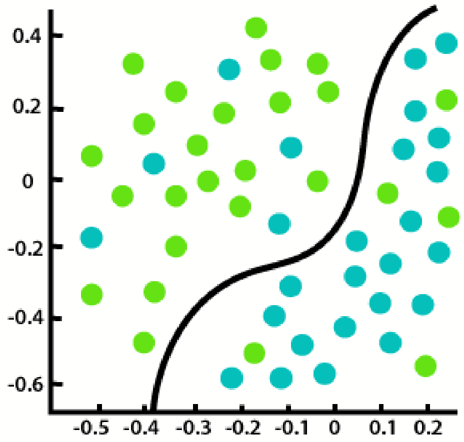


- ❑ Data-driven machine learning technology has achieved extraordinary results in numerous domains in the past decade

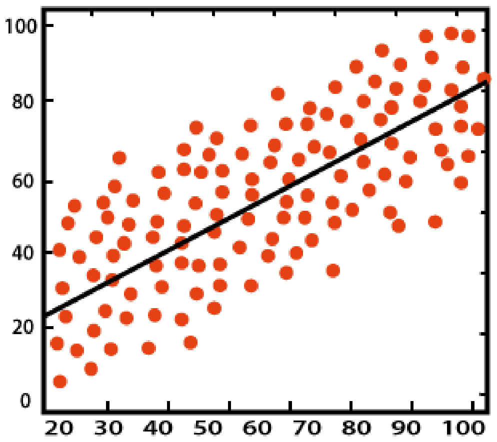
- ❑ Artificial Neural Networks (ANN) have found success in regression, classification and clustering problems



- ❑ Introduction of ANN into heat flux detection could provide a feasible method to monitor power module degradation
  - ANN structure with available features as input and output
  - Regression model to describe the mechanism
  - Classification model to identify the degradation level



Classification

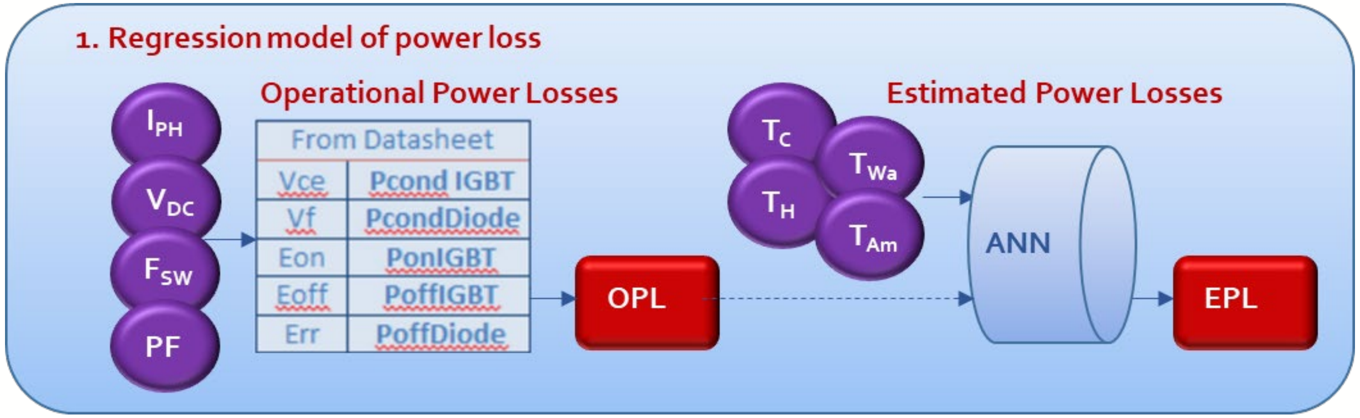


Regression

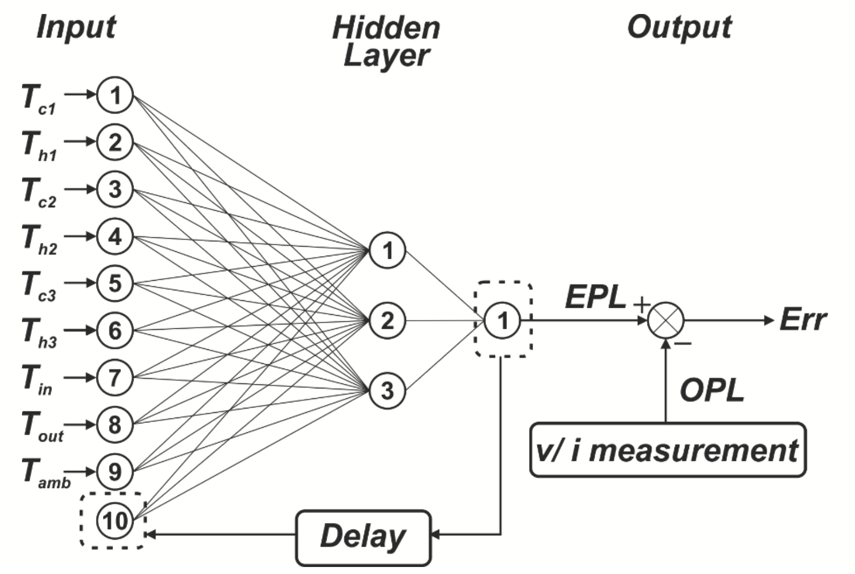
ANN-based Heat Flux Detection I

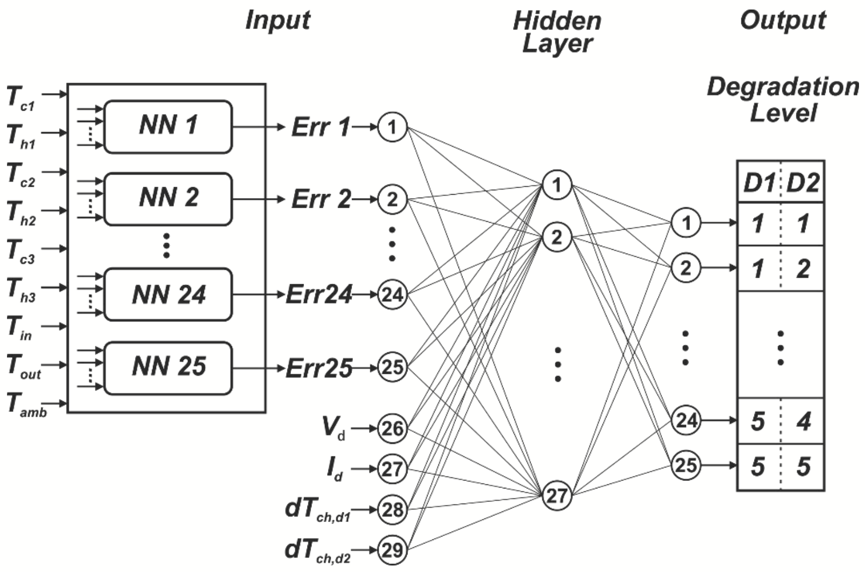
Supervised machine learning with labelled data

First stage: Regression model to quantify the power loss



Second stage: Classification model to differentiate degradation level

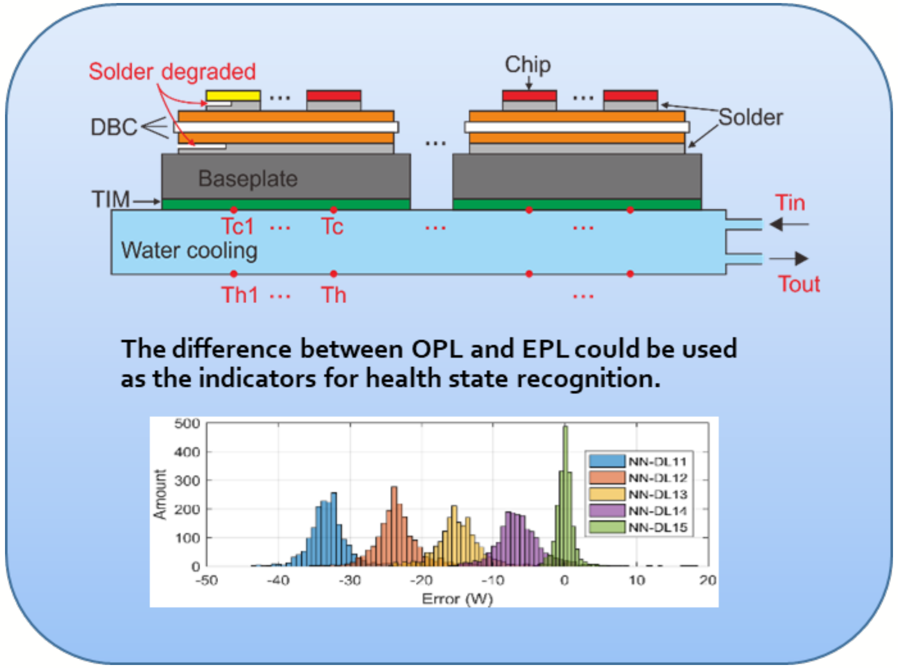


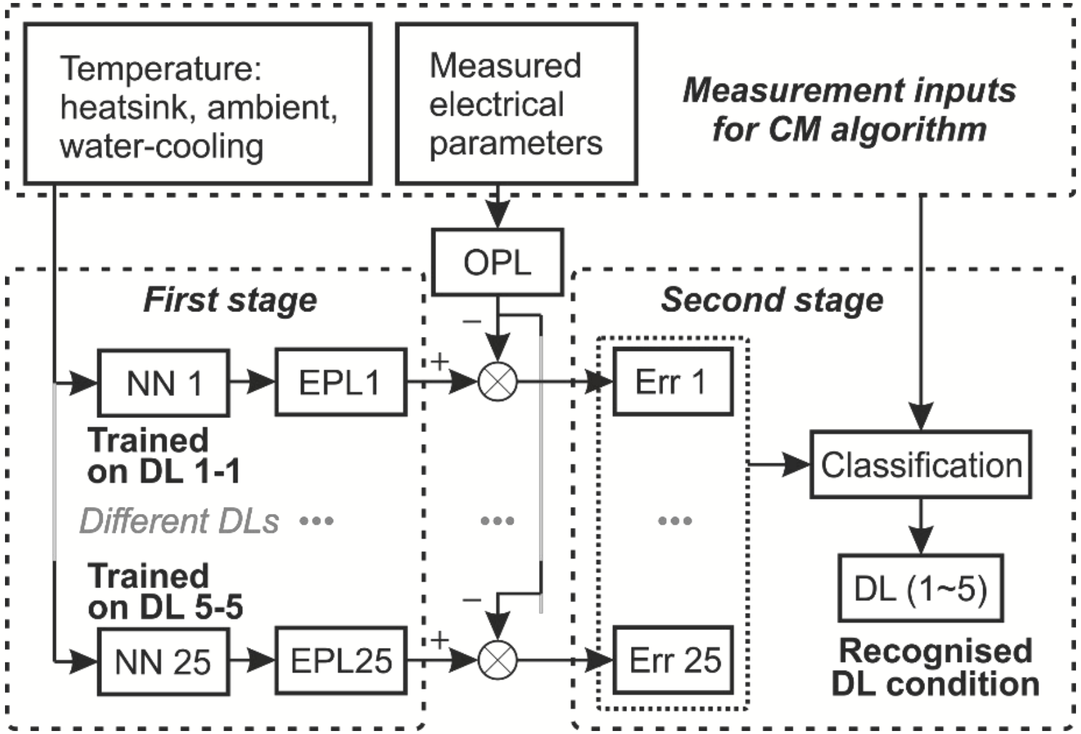


ANN-based Heat Flux Detection II

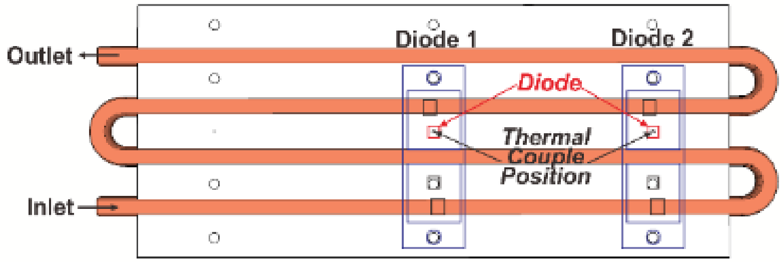
- First stage: a series of sub-NNs (neural networks), representing a **certain pattern** at different DL (degradation level). For a given **electrical operating point** labeled by OPL (operational power loss), the power losses inside the module will create a **temperature distribution** under this DL.

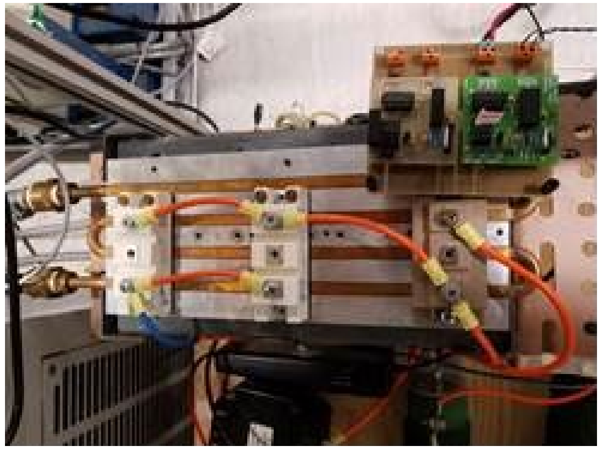
- Second stage: one NN with the inputs from all the sub-NNs at first stage to **recognise** the pattern of electrical operating point and temperature distribution and **differentiate** the related DL.

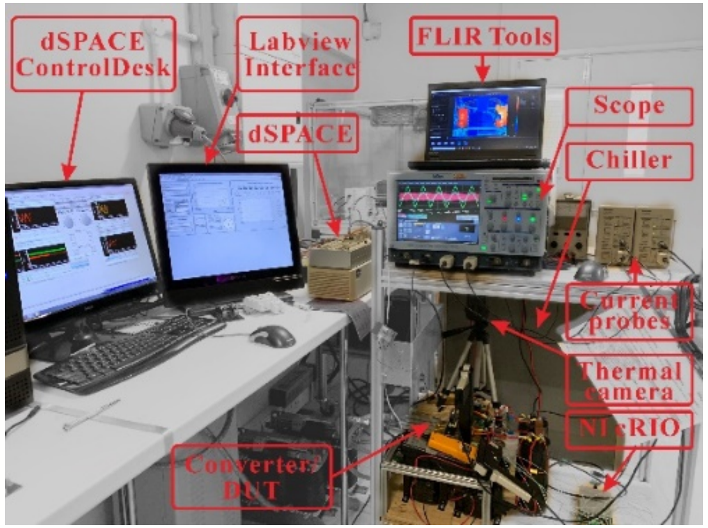


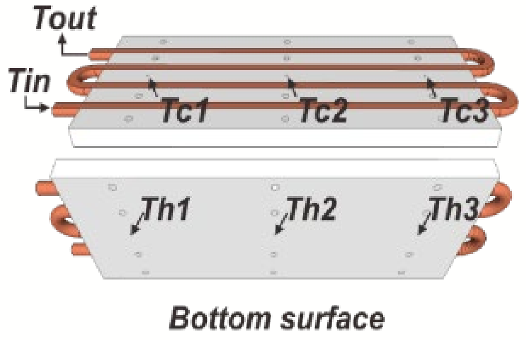


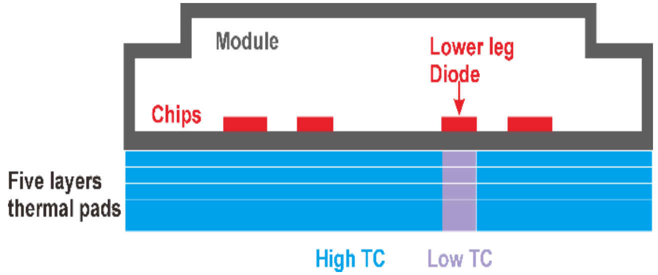
Test Rig Design

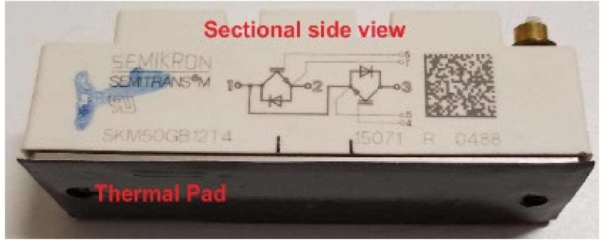










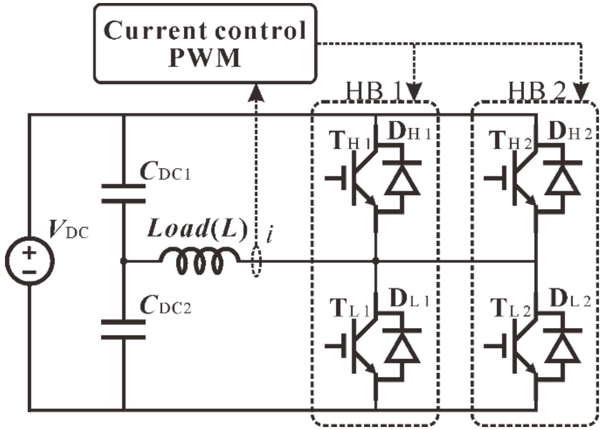


Degradation level	Number of low TC pads	Junction to case thermal resistance (K/W)	Normalized thermal resistance
DL 0	0	0.946	1 (initial state)
DL 1	1	1.052	1.112
DL 2	2	1.158	1.224
DL 3	3	1.264	1.336
DL 4	4	1.370	1.448
DL 5	5	1.476	1.560

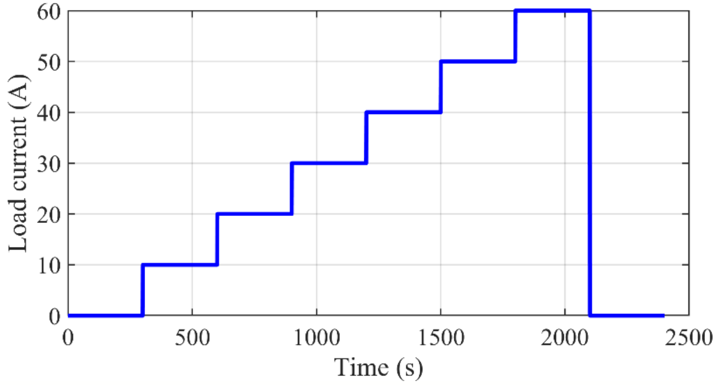
Experimental Verification Result 1

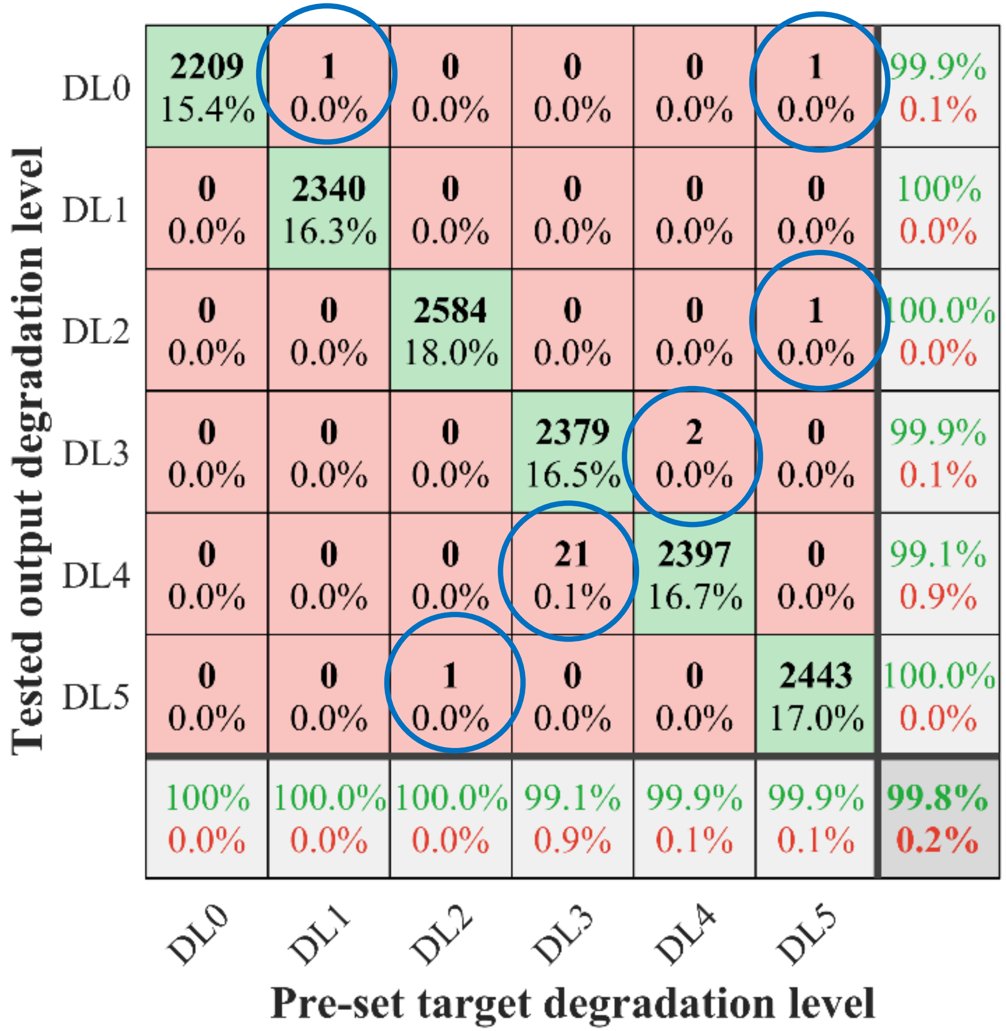
- At each degradation level (DL0,1…5), loading current increases from 10A, 20A,…,60A

- Record thermal and electrical parameters as labelled data to train ANN model for each DL



Training loading profile

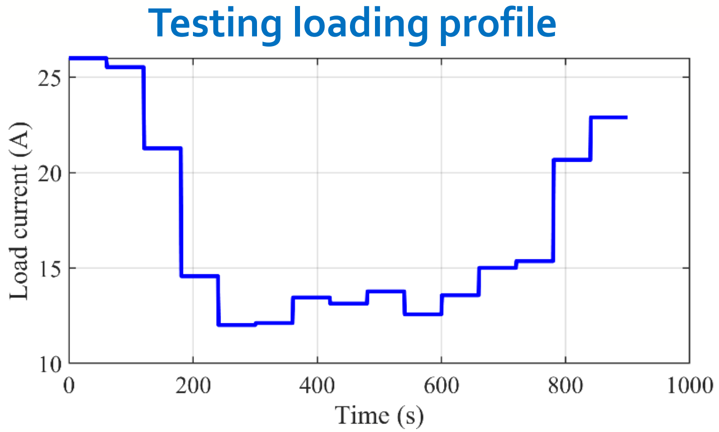


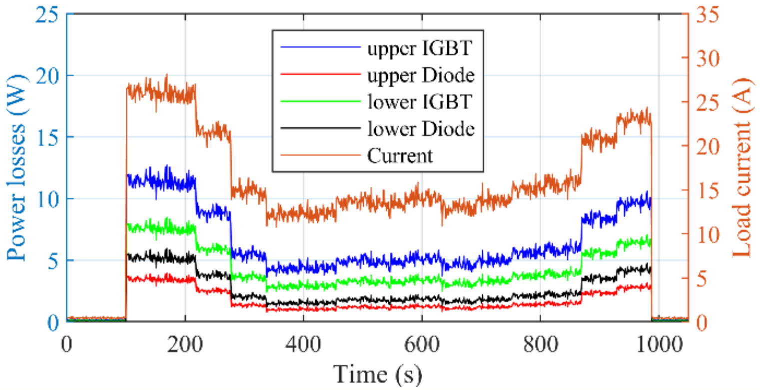


Experimental Verification Result 2

- At each degradation level (DL1…5), apply loading current profile

- Record thermal and electrical parameters to validate the trained ANN model

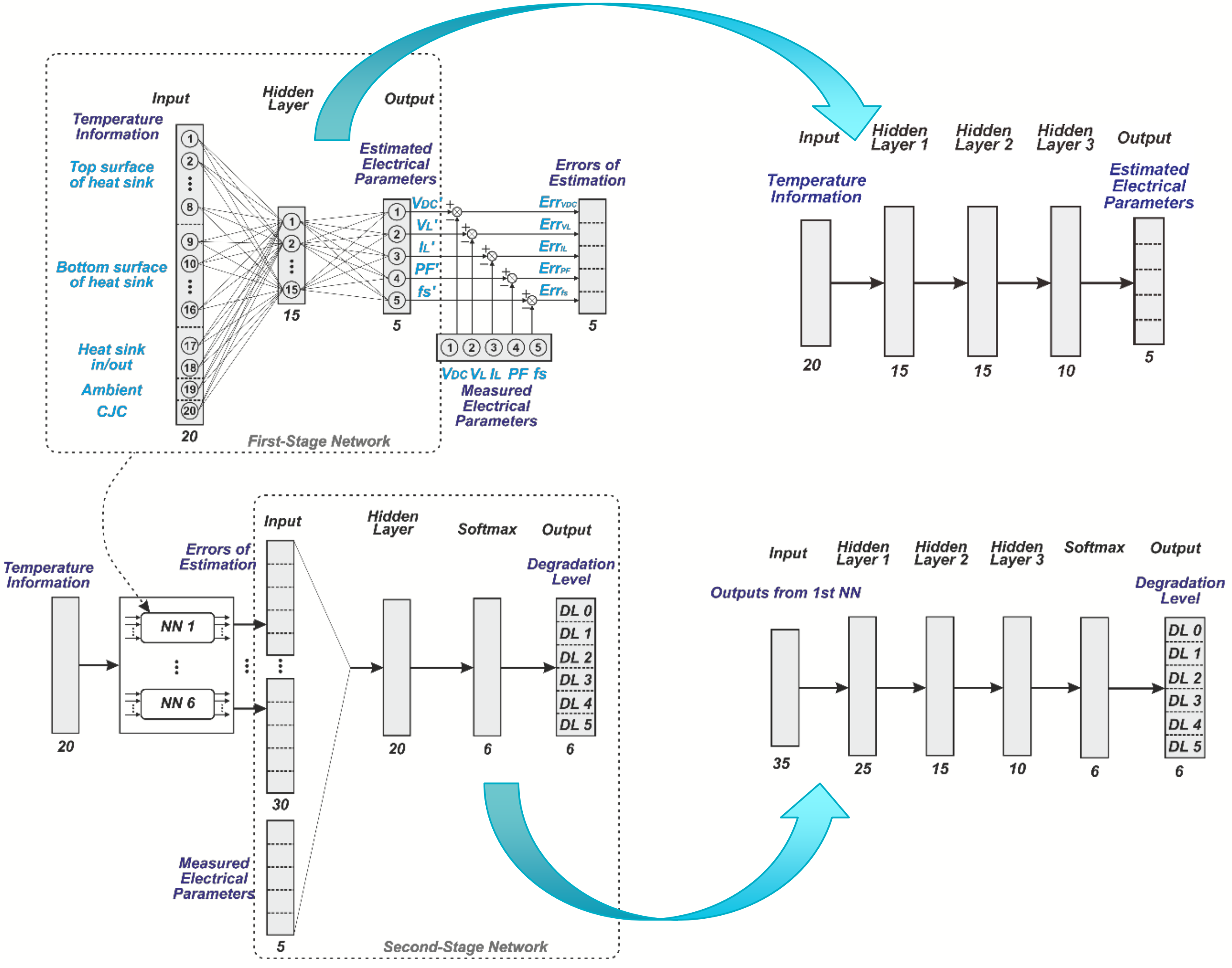




Tested output degradation level \ Pre-set target degradation level	DL 0	DL 1	DL 2	DL 3	DL 4	DL 5	
DL 0	537 8.9%	1055 17.6%	1 0.0%	0 0.0%	0 0.0%	0 0.0%	33.7% 66.3%
DL 1	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	NaN% NaN%
DL 2	1 0.0%	0 0.0%	245 4.1%	0 0.0%	1 0.0%	11 0.2%	95.0% 5.0%
DL 3	0 0.0%	0 0.0%	771 12.8%	1062 17.7%	10 0.2%	0 0.0%	57.6% 42.4%
DL 4	0 0.0%	0 0.0%	11 0.2%	28 0.5%	727 12.1%	0 0.0%	94.9% 5.1%
DL 5	0 0.0%	0 0.0%	12 0.2%	0 0.0%	455 7.6%	1083 18.0%	69.9% 30.1%
	99.8% 0.2%	0.0% 100%	23.6% 76.4%	97.4% 2.6%	60.9% 39.1%	99.0% 1.0%	60.8% 39.2%

Experimental Verification Result 3

ANN model evolution from shallow to deep neural network:



Shallow NN

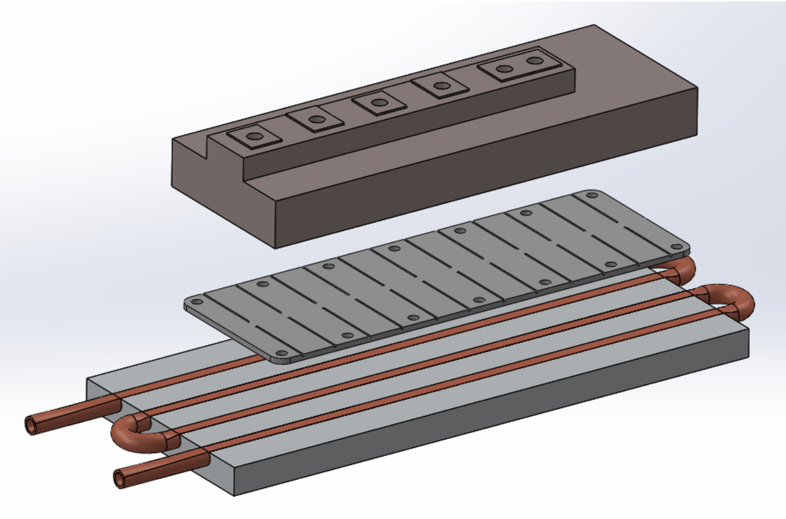
Deep NN

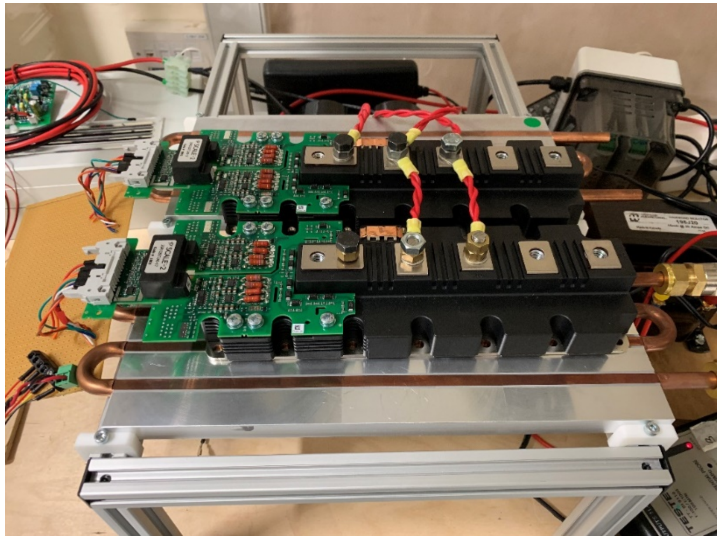
Tested output degradation level (rows) / Pre-set target degradation level (columns)

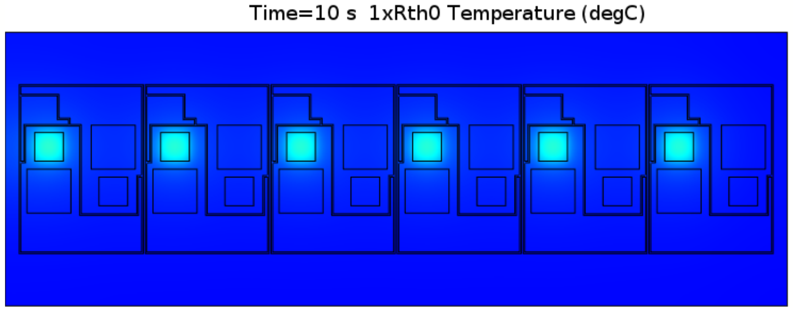
	DL 0	DL 1	DL 2	DL 3	DL 4	DL 5	
DL 0	537 8.9%	0 0.0%	1 0.0%	0 0.0%	0 0.0%	0 0.0%	99.8% 0.2%
DL 1	0 0.0%	1055 17.6%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 100%
DL 2	1 0.0%	0 0.0%	1016 16.8%	0 0.0%	1 0.0%	11 0.2%	95.0% 5.0%
DL 3	0 0.0%	0 0.0%	11 0.2%	1062 17.7%	10 0.2%	0 0.0%	98.1% 1.9%
DL 4	0 0.0%	0 0.0%	12 0.2%	28 0.5%	1182 19.6%	0 0.0%	94.9% 5.1%
DL 5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1083 18.0%	100% 100%
	99.8% 0.2%	100% 0.0%	97.8% 2.2%	97.4% 2.6%	99.1% 0.9%	99.0% 1.0%	98.8% 1.2%

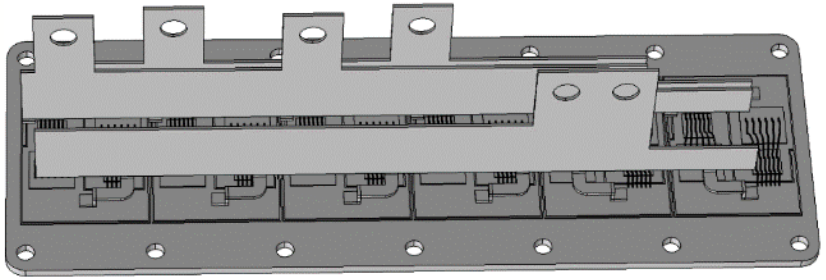
Summary and Future Work

- The deep NN-based heat flux detection method is proposed to monitor the module degradation
- The proposed method can successfully detect the degradation level even under complex operating conditions
- Future work is to verify the method with a more complicated multi-chip power module, i.e., PrimePack IGBT module









B. Hu *et al*., "Deep Learning Neural Networks for Heat-Flux Health Condition Monitoring Method of Multi-Device Power Electronics System," *2019 IEEE Energy Conversion Congress and Exposition (ECCE)*, Baltimore, MD, USA, 2019, pp. 3769-3774, doi: 10.1109/ECCE.2019.8912666.

Contact us

GLASGOW
Inovo
121 George Street
Glasgow
G1 1RD

T +44 (0)333 004 1400

BLYTH
National Renewable Energy Centre
Offshore House
Albert Street
Blyth, Northumberland
NE24 1LZ

T +44 (0)1670 359 555

LEVENMOUTH
Fife Renewables Innovation Centre (FRIC)
Ajax Way
Leven
KY8 3RS

T +44 (0)1670 359 555

HULL
O&M Centre of Excellence
Ergo Centre
Bridgehead Business Park
Meadow Road, Hessle
HU13 0GD

CATAPULT Offshore Renewable Energy