Using Machine Learning to Predict the Complete Degradation of Accelerated Damp Heat Testing in Just 10% of the Time

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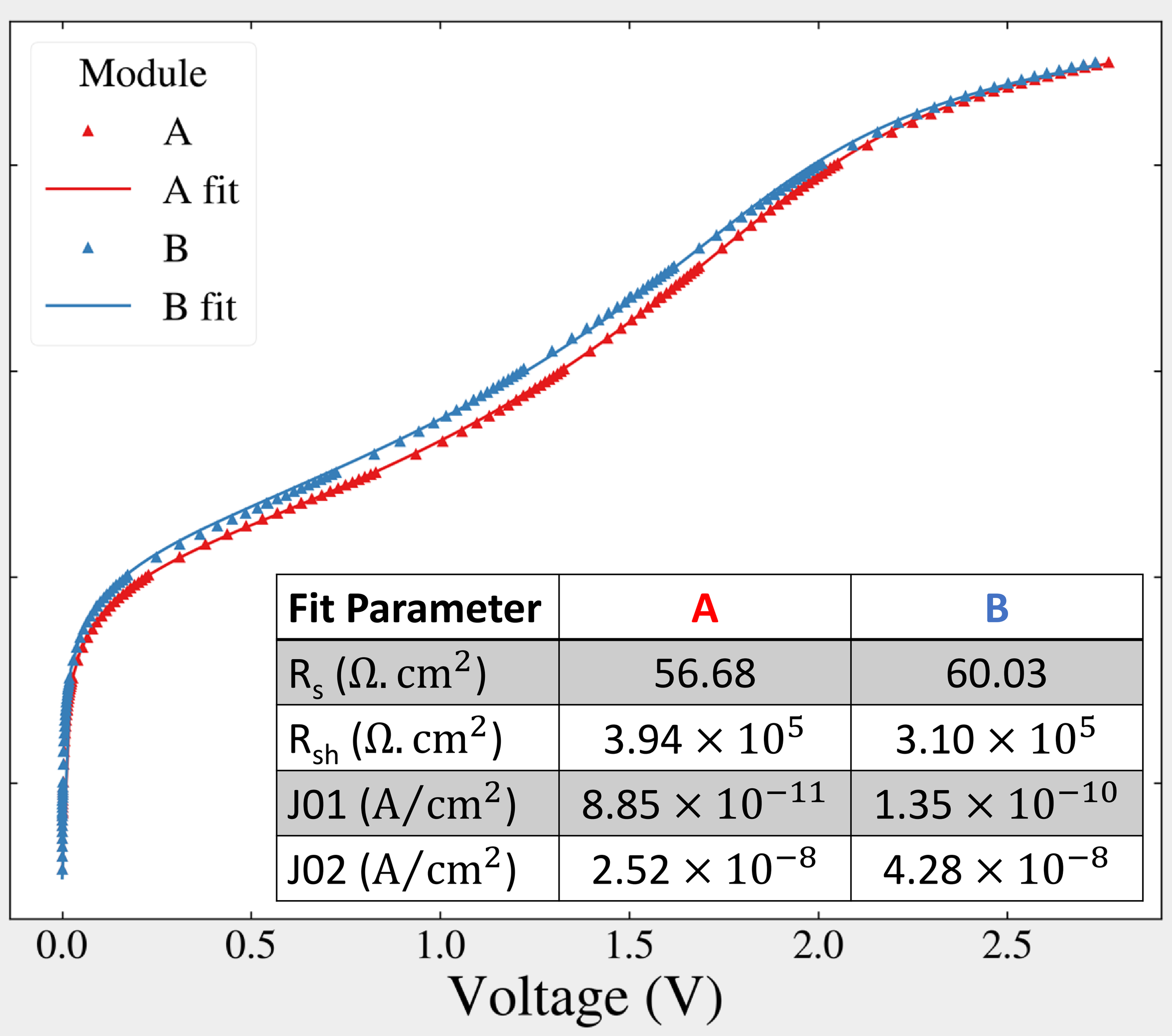
Introduction

- Precisely determining the performance of modules after 25-30 years in the field have substantial benefits for the photovoltaic market
- Accelerated damp heat (DH) testing at 85 ℃ and 85% relative humidity is a common method to study the reliability of photovoltaic (PV) modules [1]
- We propose the use of deep learning to model the changes in the performance of PV modules during the DH test
- The trained ordinary differential equation network (ODN) [2] is used to **model the complete process using ONLY the first 10% of the testing time**

Methodology

- Samples:
  - Mini-modules of four cells. Cells were taken from different efficiency bins (22.6% - 23%), including rejected cells
  - Modules fabricated using 3 mm thick soda-lime glass, an ethylene vinyl acetate (EVA) encapsulant, and a polyethylene terephthalate (PET) based backsheet
- Environmental chamber:
  - Internal dimensions 500×500×600 mm (ASLI TH-150C)
  - Modified to include an in-situ dark current-voltage (I-V) (Fig. 1) and in-situ electroluminescence (EL) imaging
- Measurements (every 48 hours, besides the in-situ measurements):
  - Light I-V measurements (SPIRE Eternal Sun)
  - EL and line-scan photoluminescence (PL) imaging (BTi M1)



Fit Parameter	A	B
R_s ($\Omega.cm^2$)	56.68	60.03
R_{sh} ($\Omega.cm^2$)	3.94×10^5	3.10×10^5
J01 (A/cm^2)	8.85×10^{-11}	1.35×10^{-10}
J02 (A/cm^2)	2.52×10^{-8}	4.28×10^{-8}

Fig. 1 – Representative examples of in-situ dark I-V measurements and their extracted fit values

Results

- Currently passed 1,500 hours of DH test of the first batch of 11 modules
- Several modules are showing signs of increased series resistance (R_s) while increased recombination can be identified in others
- As shown in Fig. 2 (b & d), the circled areas show an increase in R_s

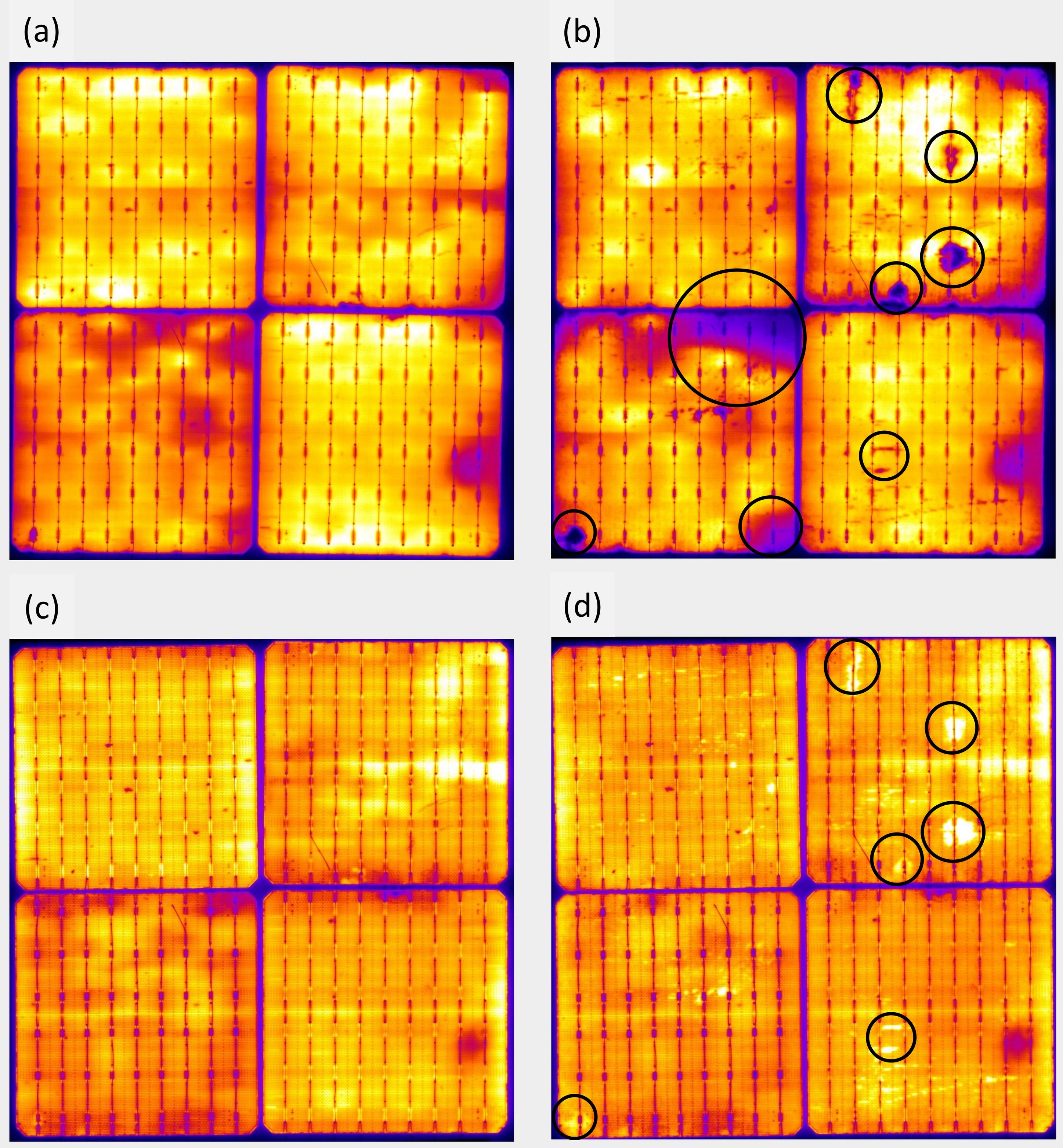


Fig. 2 – Images of a representative sample after (a) 0th hour EL, (b) 1,500th hour EL, (c) 0th hour line-scan PL, and (d) 1,500th hour line-scan PL

- The two diode model [4] was used to fit the in-situ dark I-V measurements
- Changes in the fit values over time for several samples are shown in Fig. 3
- R_s increases during the DH experiment. This aligns with the images in Fig. 2
- J_{01} increases during the DH experiment, however, the trend is found to be quite different for each module
- J_{02} decreases slightly at later hours of the DH experiment. This suggests a reduction in the edge and/ or junction recombination

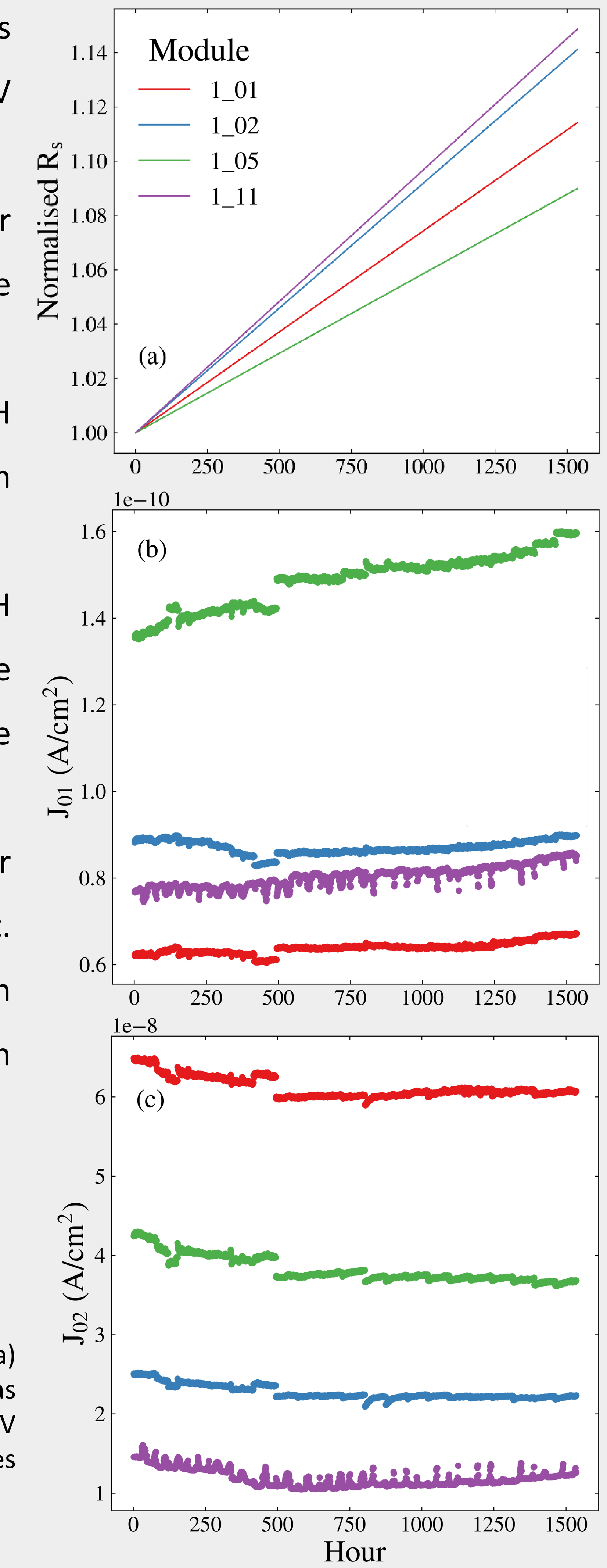


Fig. 3 – Fit values vs time for (a) normalised R_s, (b) J_{01}, and (c) J_{02} as extracted from the in-situ dark I-V measurements of several modules over 1,500 hour of DH test

Deep Learning

- ODN methodology used as an unsupervised learning approach
- Training of recurrent neural network (RNN), ODN and neural network (NN) (Fig. 4) to convert the dataset to latent states, which improves the prediction of the modules' performance over time [3]

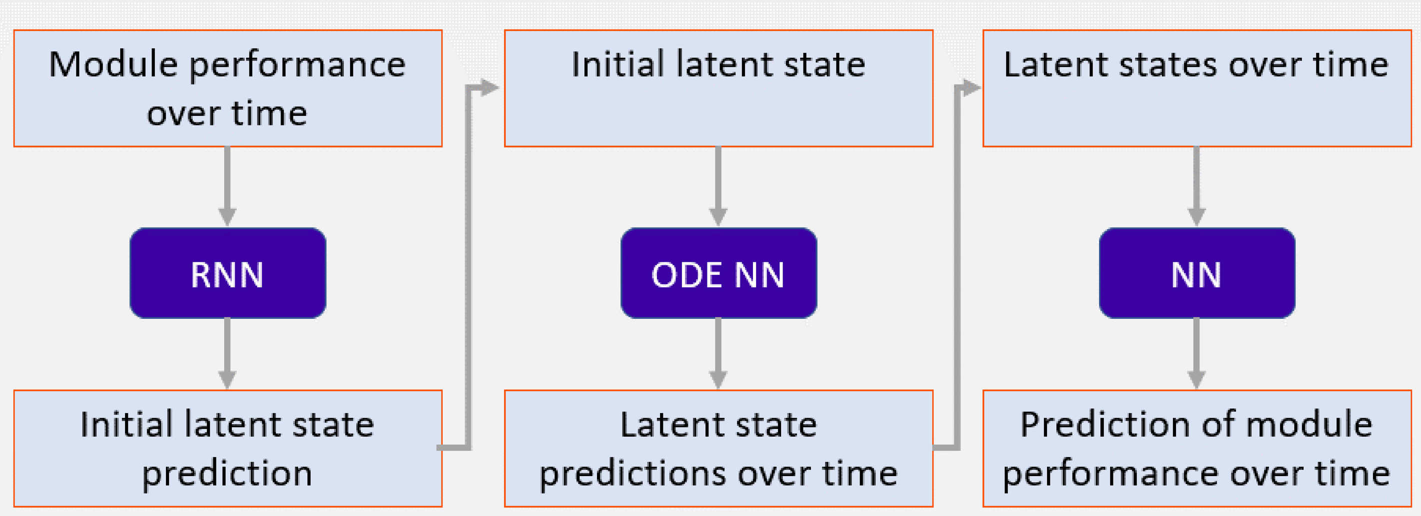


Fig. 4 – Diagram of the proposed machine learning methodology

Conclusions and Next Steps

- ODE-based deep learning methodology can **predict modules' performance** throughout the DH test
- By predicting the DH dynamics, future performance can be determined in a much shorter testing time
- The proposed method has considerable advantages for the long-term reliability and bankability of photovoltaic systems
- In-situ measurements has proved to be very useful for the extraction of high temporal resolution I-V and EL imaging data

Acknowledgements

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References

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