Using latent ordinary differential equation neural networks to predict the degradation of heterojunction PV modules at the end of damp heat tests

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1. Abstract

Photovoltaic energy is currently the most affordable form of electricity due to ongoing improvements in the efficiency and reliability of solar modules. Recently, it was suggested that 75 TW of installed photovoltaic capacity will be necessary by 2050 to reach the global decarbonisation targets. This demand increases the need for photovoltaic modules to become even cheaper and more reliable. The capability to predict the long-term field performance of photovoltaic modules is key to improving their reliability. An accurate performance prediction will also improve the bankability of utility-scale photovoltaic plants as trustworthy long-term predictions reduce uncertainties in the financing of such projects. In this study, we propose the use of latent ordinary differential equation neural network models to predict the performance of photovoltaic modules throughout a 1,500-hour accelerated damp heat test. Remarkably, using only the data collected during the FIRST 10% of the test, the proposed deep learning model accurately predicts the modules' performance through the complete test duration. This study is a critical step towards improving the reliability of fielded photovoltaic systems; the developed capabilities will help revolutionise the photovoltaic market.

2. Introduction

During the Third Terawatt Workshop organised by The Global Alliance of Solar Energy Research Institutes (GA-SERI), the imperative of deploying 75 TW of photovoltaic (PV) capacity globally by 2050 was argued [1]. This ambitious target is necessary to meet worldwide decarbonisation targets and mitigate the effects of climate change [1]. However, such significant reliance on PV energy requires further cost reduction and enhanced module reliability. Although PV energy is the most economical form of electricity today [2], further cost reduction is needed to obtain the full potential of this technology. One promising path to reduce the cost of PV systems is by further improving their reliability [3]. This can be achieved by accurately predicting their performance over their entire operational lifespan. Such predictive capability will also improve the bankability of utility-scale PV plants, as their financing often relies on projected energy output over their lifespan.

Accelerated stress tests are the conventional approach to studying the reliability of PV modules. Market approval of PV modules necessitates adherence to the International Electrotechnical Commission (IEC) 61215 standards [4]. These standards outline a set of accelerated stress tests that are required for certification. However, manufacturers often test their modules beyond the standards to further study their reliability.

A typical assessment is a damp heat (DH) test, wherein modules are placed inside an environmental chamber set to 85 °C and 85% relative humidity (RH). While the IEC 61215 standard mandates 1,000 h of DH exposure (with less than 5% performance loss), extended DH tests (up to 5,000 h, hence, 208 continuous days) are frequently conducted. These prolonged tests help to identify potential failure modes that may occur after years of field deployment [5]. Frequent degradation modes found in DH tests include discolouration and delamination of the encapsulant material, corrosion and/or breakages of cell interconnections, and degradation of the solar cells' bulk lifetime and/or surface passivation [5]–[7]. Typically, current-voltage (I-V) measurements are used to monitor the performance before and after the test, although more measurements throughout the test are sometimes performed as well [8], [9].

This study proposes the use of a single latent ordinary differential equation neural network (ODN) model to accurately predict the performance of heterojunction (HJT) PV modules throughout DH testing. The deep learning model was trained to use ONLY the initial 10% of the collected temporal data to predict the performance of the modules throughout the FULL (1,500 hours) duration. Furthermore, a single model was used to predict multiple diverse trends in the measured performance parameters. The results of this study clearly demonstrate the potential of ODN models to accurately predict the performance of PV modules throughout their years of operation in the field.

3. Methodology

A. Samples

The samples utilised in this study consisted of four-cell mini-modules (referred to as modules). The modules comprised of nine-busbar HJT cells, exhibiting measured efficiencies in the range of 24.1±0.02%. The cells were interconnected in a series-connected string configuration using rounded ribbons. Fabrication of the modules involved using 3 mm thick soda lime glass (400×400 mm), an ethylene vinyl acetate (EVA) encapsulant from Lushan, and a polyethylene terephthalate (PET)-based backsheet sourced from Jolywood.

A total of 24 modules were fabricated. Out of those, 22 were subjected to DH conditions (two sets of 11 modules each) while the remaining two modules were designated as reference samples and stored in a nitrogen cabinet. The measurements from the reference modules served two primary purposes: firstly, to validate that the observed degradation in the tested modules was indeed caused by the DH conditions; and secondly, to assess the repeatability and stability of the various characterisation systems used in this study.

B. Extended damp heat testing

The tested modules were placed inside an environmental chamber (ASLI TH-150C) for a total of 1,512 hours of DH testing. In-situ dark I-V measurements (Section C) were conducted during the DH testing. After every 72-h interval of DH testing, the chamber was ramped down to room temperature and the modules were removed for ex-situ measurements (Section D).

C. In-situ measurements

An integrated in-situ dark I-V measurement system was designed and built into the environmental chamber. The characterisation system uses a Keithley 2561A source measurement unit (SMU) linked to an arrangement of relay switchboards. These relays serve as a multiplexing system, allowing sequential dark I-V measurements of the 11 modules to be conducted at 20-minute intervals throughout the duration of the DH test. The obtained measurements were fitted with the two-diode model [10]. The resulting dataset comprised the extracted values for the two-diode saturation current densities (J_{01} and J_{02}), and the series and shunt resistance (R_s and R_{sh}) for each measurement taken over the entire 1,512 h DH testing period.

D. Ex-situ measurements

Ex-situ measurements were conducted after every 72 h DH testing period. Light I-V measurements were collected using a flash module tester (Eternal Sun; Spire) with the AM1.5G spectrum. Temperature probes were utilised to measure the modules' temperatures during the measurements. Line scan photoluminescence (PL) and electroluminescence (EL) images were collected using a BT Imaging M1 module imaging tool. A line scanning speed of 40 mm/s and a 1-Sun equivalent excitation photon flux were used to capture the PL images. At the same line scanning speed, a forward bias of 8 A was applied for the EL imaging. The reference modules were measured before the tested modules to assess the repeatability of the measurement systems.

E. Deep learning framework

We developed an ODN model to predict the multiple parameter trends collected throughout the DH test. The model follows a variational autoencoder (VAE) architecture, which capitalises on its inherent unsupervised and generative attributes [11]. A typical autoencoder model utilises an encoder to transform the input dataset into a latent vector of a pre-defined length, and a decoder, which learns to transform the latent weights back into the original input features [11]. The ODN model features three components that make up the VAE architecture. The first component is a recurrent neural network (RNN), which is tasked with transforming the initial states of the temporal data into latent weights. The second component is an ordinary differential equation neural network (ODE NN), which is trained to predict the dynamics of the given temporal data. However, the ODE NN performs this prediction in the latent space of the features. The final component is a fully connected NN that is trained as the decoder stage of the VAE. This NN converts the previously predicted latent weights into time series data. This temporal data is the prediction of the module performance over the DH test. Note that one model is trained to predict all the parameters. The overview of the ODN framework used in this study is shown in Fig. 1.

At the time of writing, the performance parameters that were used to train the ODN model are the open circuit voltage (V_{oc}), the mean pixel intensity of the EL images ($\overline{\mathrm{EL}}$), module efficiency, and J_{02}. The dataset and the time array (values corresponding to the 72 h periods) were first normalised to the maximum value for each parameter. A single ODN model was then trained on the normalised data such that it learns the performance of the PV modules at each given time stamp. During testing, only the first 10% (0 – 144 h) of the measured four parameters collected during the DH test were provided to the model as the initial states of the samples. The model used this initial data to predict the performance of all four parameters throughout the entire DH test (0 – 1,512 h). Therefore, a single model predicts the expected values of all the parameters at each 72-h time stamp throughout the DH test from just the first 10% of the measurement duration.

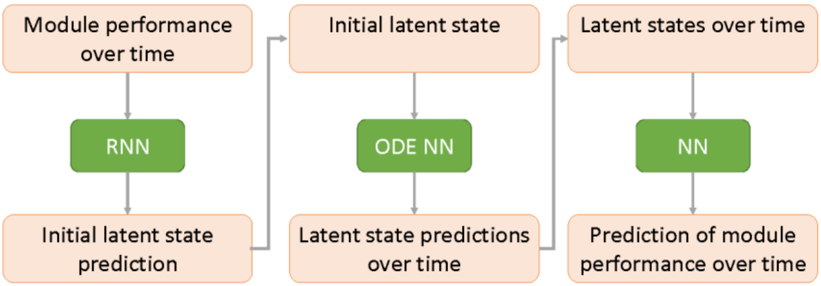

Figure 1. Flowchart of the ODN model used in this study.

4. Results

The EL and line scan PL images of a representative module are shown in Fig. 2. The degradation observed in the HJT modules caused a global decrease in the luminescence intensity. Localised areas of increased degradation at the busbars, likely due to corrosion, are clearly noticeable as well as other local sites (white circles), likely due to defects [5], [7]–[9].

The results of the four parameters predicted by the ODN model are shown in Fig. 3. Only 10% of the module measurements are used as input (red stars). The predicted performance throughout the DH test is shown by the green line. To validate the prediction, the measurements obtained throughout the DH test (grey dots) are also shown. The mean absolute percentage error (MAPE) was used to quantify the error in the validation data. As expected, there is a decreasing trend seen in the measured data [Figs. 3(a-c)] and an increasing exponential trend in J_{02} [Fig. 3(d)] throughout the DH test. Although the four parameters have differing trends and initial states, the single ODN model predicted the performance of all trends with very low MAPE using only the first 10% of the temporal data.

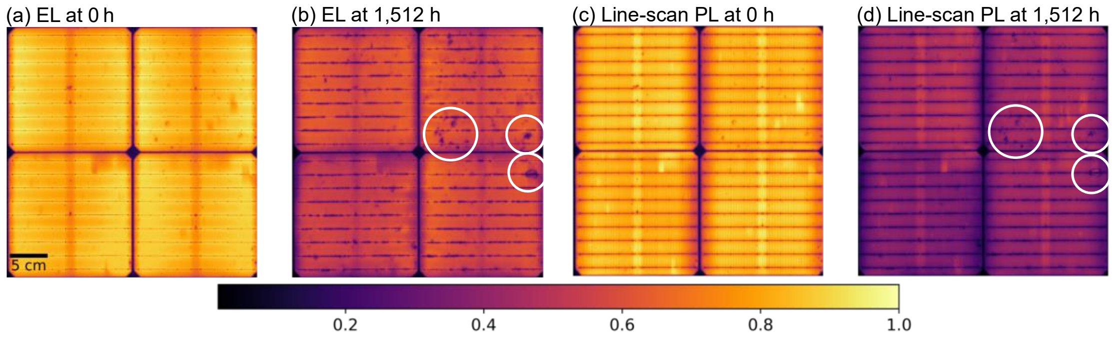

Figure 2. Normalised images of a representative sample after a DH test of 85°C and 85% RH. EL at hours (a) 0 h and (b) 1,512 h, and line-scan PL at (c) 0 h and (d) 1,512 h. The white circles highlight some of the localised degradation spots.

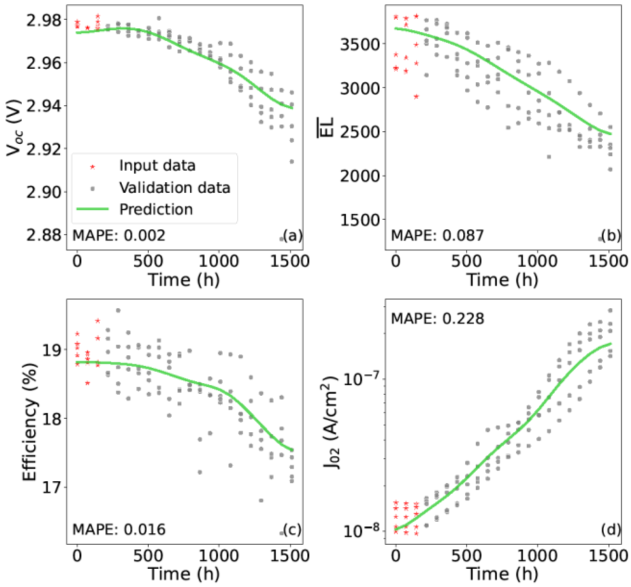

Figure 3. Several test samples with their measured trends and the predicted trends versus time for (a) V_{oc}, (b) mean EL intensity, (c) efficiency, and (d) J_{02}.

5. Conclusion

This study proposes the use of deep learning to learn the dynamics of DH degradation, predicting the performance of PV modules throughout accelerated stress tests. A single ODN model was trained to predict four different electrical parameters that degraded throughout the extended DH testing of HJT modules. Given just the initial 10% of the measured temporal data, the ODN model accurately predicted the degrading trends in the performance of the modules. This approach is also easy to train and run on consumer-grade computing processors, making it easy to implement. This study is a critical first step towards predicting the performance of fielded modules throughout their lifetime. Such a capability will bring significant advantages for the long-term reliability and cost of PV systems, contributing to the immense task of deploying 75 TW of solar energy by 2050.

6. References

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