Advanced Silicon - Lower photovoltaic cost by a combination of luminescence images and machine-learning

Project results and lessons learnt

Lead organisation: University of New South Wales, Sydney

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Executive Summary

The overall aim of this project was to reduce the cost of characterisation tools and increase their throughput as traditional characterisation tools are slow and expensive to maintain. To overcome these problems, innovative techniques were developed. These methods are based on machine learning (ML) and luminescence images of solar cells. Since luminescence imaging systems are expected to be installed in >80% of production lines by 2029 and ML algorithms can be easily incorporated into inspection systems, the developed techniques can be efficiently installed in almost any production line.

For the following applications, multiple ML-based algorithms were developed during the project's timeline:

- Solar cell sorting using luminescence images
- Automated fault classification using luminescence images
- Degradation prediction using ONLY the first 10% of the measurements
- A commercialisation plan was developed in collaboration with the industry partner to accelerate the adoption in the production line.

Besides the stated milestones, the project supported the development of several novel ML applications:

- High-resolution luminescence imaging enables the identification of small defects and faults. One method to increase image resolution is using expensive hardware. In contrast, this project developed cost-effective ML-based algorithms to increase image resolution. It has been shown that ML-based algorithms outperform traditional image processing-based techniques.
- Development of a hybrid model for the prediction of key electrical parameters. Hybrid models (a combination of empirical expressions and ML) often outperform empirical expressions or pure ML models. Empirical expressions frequently do not take into account the complexity of solar cells (such as non-uniformity) and are commonly time intensive, whereas ML models can sometimes focus on correlations that are already known instead of those that are hidden.

Project Overview

Project summary

At the end of any solar cell production line, the electrical properties of cells are measured using state-of-the-art current-voltage (I-V) measurements. I-V testers need to be constantly updated as cell technology changes. Moreover, their throughput is limited compared to the current demand of the industry. Therefore, the first part of the project aimed to replace I-V testers with a machine learning (ML) luminescence image-based method. Within this part of the project, our prediction results for I-V parameters achieved an R^2 score of 93% and a root mean square (RMSE) of less than 0.10% absolute cell efficiency, both are considered excellent outcomes.

To increase the overall module efficiency, underperformed cells need to be identified and rejected accordingly. Simple manual inspections are being used for this process which is time-consuming and requires an expert to perform this task. Therefore, the second part of the project aimed to automatise this manual process using ML which would increase the throughput of the production lines and reduce the cost of the inspection. The developed approach achieved an outstanding result with an overall accuracy of 99.2%.

The reliability of photovoltaic (PV) modules is a critical aspect of the cost of PV systems. Currently, damp heat tests are performed to evaluate the reliability and durability of the modules. These tests often take 1,500 hours and more. Therefore, to reduce the measurement time, deep learning-based algorithms were developed to predict the extent of degradation using only the initial 10% of the measurements. The developed approach predicts the performance at the end of the test, achieving an excellent mean absolute percentage error of ~0.005.

Project scope

The Intergovernmental Panel on Climate Change (IPCC) sets a clear target that one-third of global energy must come from renewable sources by 2030. To meet this target, PV-generated electricity must play a key role. Due to technological advances achieved in the past decades, PV has become the cheapest form of available renewable source. However, to increase its widespread adoption, the cost of PV systems must further decrease. Therefore, in this project, cost-effective and high throughput characterisation tools were developed.

The main barriers to the traditional characterisation tool, such as I-V testers, are their maintenance costs, throughput, and limited provided information. This project created the knowledge that enables the development of multiple ML algorithms that predict efficiency from luminescence images, automate the inspection process, classify the faults, and predict the extent of degradation.

Outcomes

The project achieved all the milestones. It advanced knowledge in the field of PV to support the replacement of illuminated I-V measurements currently used in solar cell manufacturing lines with much faster and cheaper methods. The developed ML algorithms can also identify various loss mechanisms using luminescence images to assist with the early identification of problems in the production lines.

The project supports the development of cost-effective silicon solar cells through the development of automated inspection methods aimed at improving and speeding up fault classification and sorting processes currently used in solar cell manufacturing.

Seven journal papers were published (and two additional papers are currently under review). To share the work with the PV community, 25 conference papers were presented at the leading PV conferences. Students of this project received serval accolades in the form of the **Best Student Paper Award**, **Best Poster Award**, Finalist for the Best Student Paper Award (twice), and Finalist for the Best Poster Award. Moreover, one of the undergraduate students of this project received the **Best Undergraduate Thesis Award** (the School of Photovoltaic and Renewable Energy Engineering, UNSW) and another PhD student received the **Dean Best PhD Thesis Award** (UNSW, 2023).

The developed algorithms are shared in a public hosting service for software development (GitHub):

- https://github.com/acdc-pv-unsw/LumiNet
- https://github.com/acdc-pv-unsw/Tile-Level-Defect-Detection
- https://github.com/acdc-pv-unsw/Crack-and-Finger-Failure-Detection

Integration of fault classification and detection methods with existing characterisation tools will significantly improve existing inspection tools and services. For this, a commercialisation plan was prepared.

Transferability

The developed technology to automate fault classification of solar cells can easily be transferred to the inspection of PV modules and can assist with end-of-life decisions.

The developed approach for degradation prediction can be applied to the inspection of utility-scale PV plants.

Conclusion and next steps

The developed methods and techniques can reduce the cost of characterisation tools and increase the reliability of PV systems.

The developed techniques to replace I-V testers can be applied in half-cells, busbar-less, or shingled cells. These cells are hard to measure due to their structure, therefore, ML and luminescence imaging methods have great potential to estimate mismatch loss which is currently not done in production lines.

The challenge of PV module end-of-life (EoL) management is receiving increasing attention from PV plant owners, assets management and O&M (operations and maintenance) companies, module manufacturers, and government regulatory organisations. Ultimately, determining when PV modules reach their EoL is not straightforward as often they still produce power when this question is asked. Deciding their future (reuse, resell, recycle) is also complex. The outcomes of this project (the developed automated fault classification), along with other image processing algorithms, can be used to determine the EoL of PV modules and their preferred future paths.

Despite the frequent collection of electrical and weather data from nearly all PV plants in Australia, it is uncommon for this data to be utilised to enhance plant performance and minimise potential losses such as degradation and soiling losses. The developed approaches in this project can detect and classify performance degradation at an early stage and predict faults so that appropriate action can be taken even BEFORE faults occur and cause damage. The implementation of these ML algorithms will help to overcome these challenges and minimise the financial losses incurred from degradation and soiling.

Lessons Learnt Report: Cost-effective ML-based approaches to increase luminescence image spatial resolution

Project Name: *Advanced Silicon - Lower photovoltaic cost by a combination of luminescence images and machine-learning*

Knowledge Category:	Technical
Knowledge Type:	Technology
Technology Type:	Solar PV
State/Territory:	NSW

Key learning

Two key learnings are identified: (1) image enhancement algorithms based on ML outperform traditional image processing algorithms to increase the spatial resolution of luminescence images, and (2) the developed ML-based algorithms learn to improve the image resolution even in cases that are significantly different from the images used in the training phase.

Implications for future Projects

To increase the spatial resolution of luminescence images, ML-based algorithms can be used instead of image processing-based algorithms. The utilisation of such algorithms has the potential to successfully improve the resolution of images that are very different from those used for the training. This effectiveness may lead to increased adoption of ML-based solutions as a replacement for costly hardware-based alternatives.

Knowledge gap

Image metrics play a fundamental role in assessing enhanced super-resolution images. While various metrics have been proposed, it is acknowledged that none of them accurately measures the quality of an image. Hence, the existing metrics have severe limitations in effectively quantifying the reconstructed images in relation to human visual perception. There is an urgent need to develop more accurate image metrics to facilitate the evaluation of image quality.

Background

Objectives or Project requirements

Luminescence imaging is a fast and non-destructive method to spatially resolve the non-uniform electrical properties of solar cells. The key factor determining the effectiveness of these images is their spatial resolution, which determines the smallest identifiable features. This stage of the project aimed to computationally enhance the spatial resolution of luminescence images with minimal cost. By utilising ML-based approaches, a simple and effective method of reducing the cost of luminescence imaging systems and increasing their capabilities was developed.

Process undertaken

A deep learning-based algorithm enhanced super-resolution generative adversarial networks (ESRGAN) was used to enhance the luminescence image resolution. The network used 26,500 luminescence images of mono-crystalline industrial solar cells. These images have a resolution of 520×520 and were used as the high-resolution image target. Low-resolution images (130×130) were created by down sampling the high-resolution images. This paired dataset was used to train the network. An unseen dataset of almost 440 images was used to test and evaluate the performance of the trained network. The developed method is also compared to a baseline approach (bicubic interpolation) that is often used to generate high-resolution images.

Supporting information

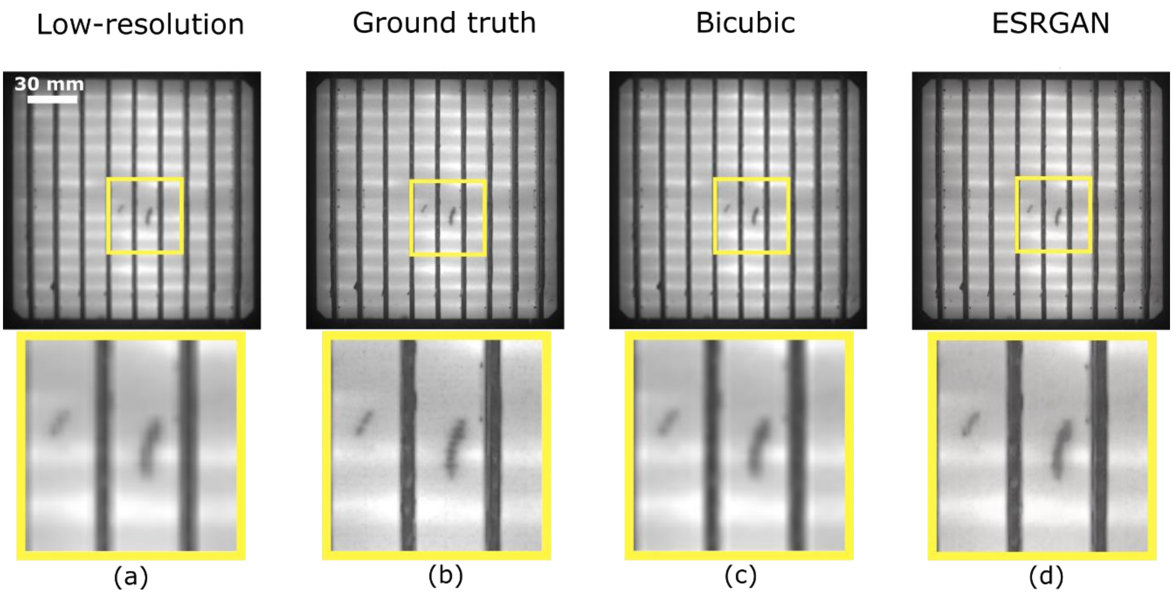

Figure 1: A representative low-resolution image (130×130 pixels) from the test dataset (a), the corresponding ground truth image [(b), (520×520 pixels)], and upsampled images by a factor 4×4 using bicubic (c) and ESRGAN (d). Pixel counts for all the images range [0, 255].

Figure 1 presents representative luminescence images of a solar cell from the test dataset containing distinct defects. Figure 1(a) shows the low-resolution image created computationally from the ground truth image, shown in Fig. 1(b). The resolution is then computationally enhanced using the two techniques: a bicubic interpolation [Fig. 1(c)] and the developed enhanced super-resolution generative adversarial network (ESRGAN) [Fig. 1(d)]. To aid visual inspection, zoomed-in images of regions with distinct defects are presented below each image. It can be clearly seen that even the smallest features such as the pins along the busbar or a scratch mark are successfully reconstructed.

Figure 2 presents representative low-resolution images (a), ground truth images (b), as well as corresponding enhanced images using the bicubic interpolation (c), and ESRGAN (d). Results show that when using ESRGAN, all the artificially created marks are successfully up sampled and the ESRGAN-generated images are of superior quality compared to those based on the bicubic interpolation method.

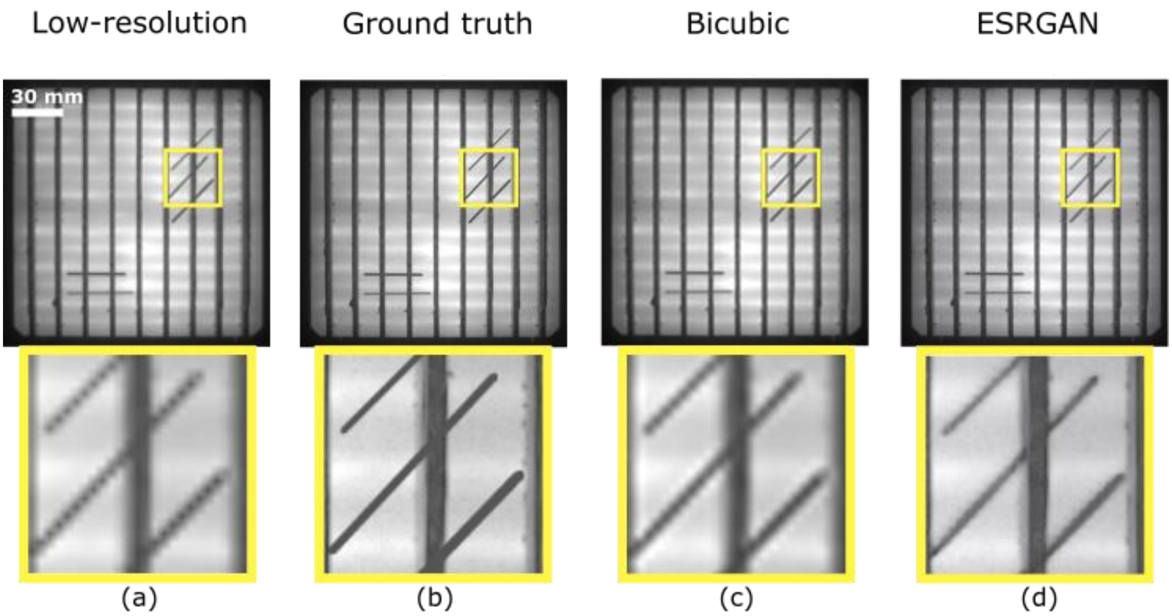

Figure 2: Low-resolution image (a) with artificial, manually added marks that were not present in the training dataset, the corresponding ground truth image (b), and enhanced images using bicubic (c) and ESRGAN (d). Pixel counts for all the images range [0, 255].

Lessons Learnt Report: Combined physical and ML model outperform pure ML model

Project Name: *Advanced Silicon - Lower photovoltaic cost by a combination of luminescence images and machine-learning*

Knowledge Category:	Technical
Knowledge Type:	Technology
Technology Type:	Solar PV
State/Territory:	NSW

Key learning

The accuracy of physical models or empirical expressions can be improved using ML models. The empirical expression is used for initial estimation whereas the ML model improves its accuracy further. The hybrid approach is found to be much more successful than either empirical or pure ML model approaches.

Implications for future Projects

Instead of applying a pure ML model, empirical expressions can be used for an initial estimation of that parameter while the ML model is trained to predict the residual. This can provide better results with, perhaps, less amount of data.

Knowledge gap

Hybrid models, which integrate both empirical equations and ML techniques, are demonstrated to provide superior performance in comparison to pure empirical equations or ML models alone. However, in order to fully assess the robustness and reliability of these models, it is important to evaluate their performance using datasets obtained from different production lines. This will provide insights into the generalisability and applicability of the models across different industrial settings.

Background

Objectives or Project requirements

The fill factor (FF) is one of the key electrical parameters describing the performance of solar cells. The FF is directly proportional to the power conversion efficiency of a solar cell (higher FF leads to higher efficiency). It can be computed from the ratio of the maximum power to the product of the short circuit current I_{sc} and the open circuit voltage V_{oc}. One of the ways to extract FF is using Martin Green's empirical equation. In this stage of the project, a hybrid approach is assessed to estimate the fill factor of solar cells from luminescence images.

Process undertaken

The process consists of two stages: (1) FF estimation through an improved empirical approach using normalised values of V_{oc}, series resistance (R_s), and shunt resistance (R_{sh}); and (2) reduction of errors through an ML framework. The accuracy of this hybrid approach is then compared with predictions based on (1) a purely empirical model (based on V_{oc}, R_s, and R_{sh}), and (2) a pure ML-based model.

Supporting information

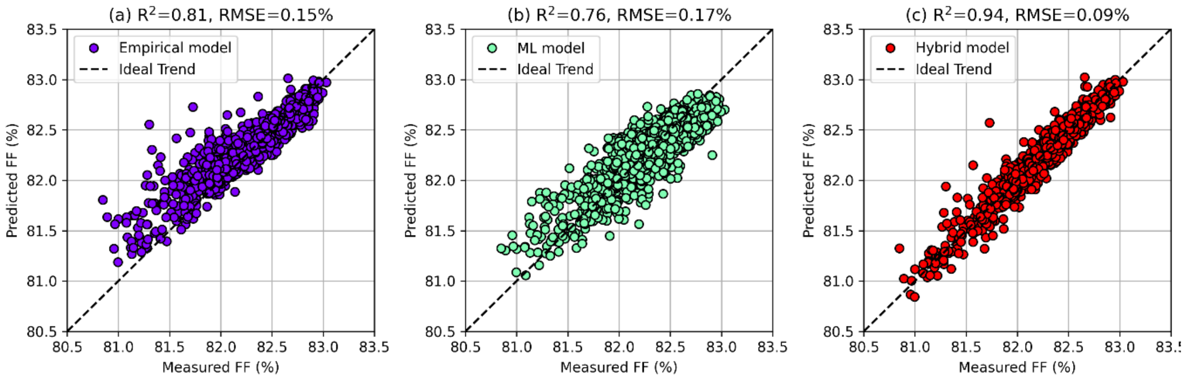

Figure 3: Predicted FF vs measured FF using (a) the empirical model, (b) the ML model, and (c) the hybrid model.

Figure 3 shows the predicted FF by the pure models and the hybrid model as a function of the measured FF of the validation set (2,000 cells). Figure 3(a) shows the accuracy of the empirical model which makes use of only the empirical expressions. The R^2 and RMSE are 0.81 and 0.15%, respectively. Figure 3(b) shows the accuracy of the pure ML model that directly estimates the FF from the images. A relatively lower R^2 is observed compared to the base model, however, the RMSE values of both pure models are almost the same. Figure 3(c) shows the accuracy of the proposed hybrid approach. A significant improvement in both R^2 and RMSE is observed. The results indicate that better performance is observed when the empirical expressions are used to estimate a base FF and then an ML framework is applied. The proposed hybrid approach has great potential in accurately estimating the FF directly from luminescence images, which in turn can be applied in optimising modern industrial manufacturing lines.