Automatic IV Curve Diagnosis with Deep Learning

Haohui Liu, Manav Arora, Kang Jian, Lu Zhao
Envision Digital International, 098632, Singapore

***Abstract*—IV curve tracing is a useful method for diagnosing PV array underperformance problems. Its shape and values can reveal internal health issues of devices, caused by degradation, mismatch, cell cracks, or external issues of operating environment, such as shading and soiling. In recent years, there is a trend for string inverters to provide IV scanning function, which enables large scale high throughput IV curve diagnosis for PV farms. For this application, it is important to have automatic diagnosis and reporting instead of manual interpretation. In this work, we propose a diagnosis framework based on deep learning to classify various DC underperformance issues or faults from IV curves. The initial model training is accomplished by simulation of IV curves for a wide range of possible scenarios. Preliminary results indicate that the model is capable of discerning major classes of issues to a very high degree of accuracy.**

Keywords—photovoltaic, IV curve, deep learning, AI, underperformance diagnosis

I. Introduction

PV installation is expected to grow at a rapid pace, reaching a scale that is impossible to manage in traditional, manual ways. PV farms are generally made of a large number of PV strings. In the field, numerous DC health issues may impact performance. It is much desirable to find out these underperformances and optimize performance. Due to the scale of PV installation, even a small percentage of improvement will lead to immense economic benefits. Time series performance monitoring is the primary means to ensure good operation. However, certain problems are hard to diagnose from performance data alone. This is because only the maximum power point information is recorded when PV is in operation, hence much information about system response is lost. IV curve scanning, as an advanced diagnosis method, can add back the lost dimension of information. In many cases, it helps to pinpoint root causes of low performance.

Traditionally, IV response is obtained manually with handheld tools such as Solmetric IV tracer. In recent years, more and more inverter manufacturers had integrated this function into their string inverters, enabling remotely triggered scanning to read off the IV curve for each MPPT. In this way, even large PV systems can be scanned in a relatively short time and in an automated fashion. This is extremely helpful for operation and maintenance (O&M), especially for unmanned remote sites. However, interpretation of IV curve requires skills and significant domain knowledge, which tends to become the new bottleneck. Therefore, automatic diagnosis of IV curves is important for fully realizing the value of such application. Although some inverter monitoring platforms give rudimentary diagnosis report for the scanned IV curves, the reliability and derivable insights are limited. There is hence still a large room for improvement.

Many methods for IV curve analysis and diagnosis had been proposed in the literature [1]–[7]. However, they are generally not "production friendly" due to the following reasons:

- The methods may have elaborate steps or computationally expensive models that are not easy to implement in production environment.
- Intricate procedures and models reduce robustness of these methods for real world field data.
- The pre-processing steps involve sophisticated methods for normalization or correction. Furthermore, this has high dependence on accurate measurement of extensive set of parameters such as module temperature and irradiance, which may not be available in practice.
- Models are developed, calibrated, and tested on very specific system configurations, which may not generalize well.
- Some models are specialized for certain types of catastrophic faults, but do not address the broad spectrum of possible underperformance scenarios that are relevant for solar asset management needs.

In this work, we develop a more general framework based on big data and deep learning for diagnosing underperformance issues commonly encountered in PV plants. First, we summarize the various scenario categories that are of interest to O&M personnel. This classification considers the practical needs for O&M decision making and is more refined than any previous schemes proposed so far. Subsequently, extensive IV curve simulation is done by sampling from the possible parameter space associated with each scenario. The simulated dataset is used for training the initial deep learning model to extract relevant IV curve features and thus classify different underperformance categories. Preliminary results indicate that this approach is feasible for classifying IV curves based on their shape and pattern alone, without extensive input of environment measurements. For better accuracy, the model can be easily extended to include inputs such as irradiance level, temperature, and other information from time series performance monitoring. Once labeled field data becomes widely available, the model can be further enhanced using transfer learning with real world data.

II. Methodology

A. *IV curve classification*

Underperformance instances can be due to both internal and external issues. Here, internal issues refer to device health problems such as mismatch, cell cracks, resistance issues, degradation, or acute electrical faults such as line-to-line fault. External issues refer to undesirable effects caused by operating

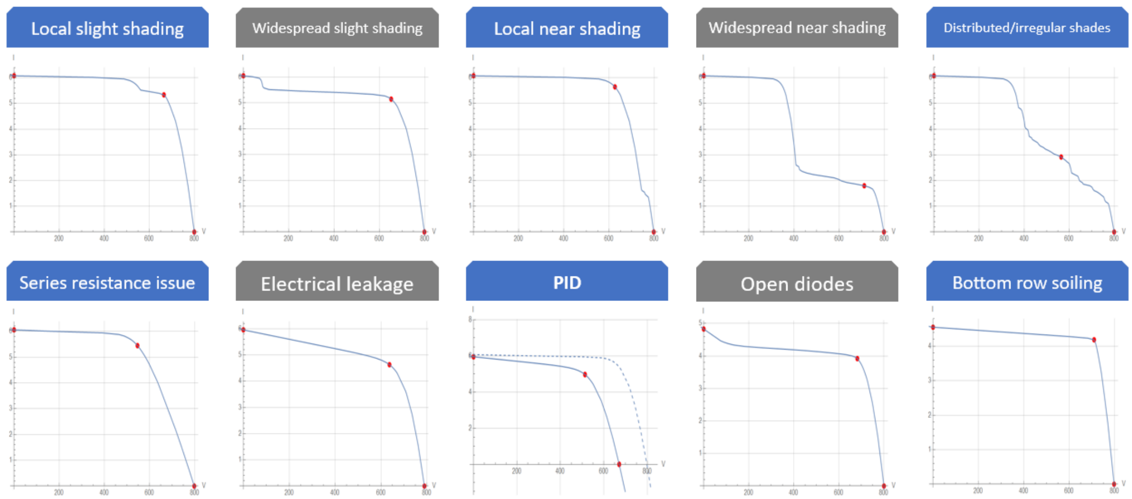

Fig. 1. Illustration of IV curve patterns under various types of underperformance / fault scenarios.

environment, mainly shading and soiling. In some cases, they may lead to significant drops in performance level, which are eventually detected from time series performance monitoring. In this case, IV scanning is useful for pinpointing possible root causes to enable a more targeted site inspection and action. However, in many cases they may not lead to noticeable drops in performance but are nonetheless important to be discovered early. In this case, IV scanning is even more integral for complementing routine performance monitoring.

To our knowledge, none of the existing classification schemes are adequate or comprehensive enough to cover the possible underperformance or fault cases, and at the same time offering useful insights for field operation. Based on common O&M needs and scenarios from both utility scale and C&I rooftop solar systems, we propose the following categories for automatic IV curve diagnosis (Table 1). Shading and surface coverage are the most encountered external issues in the field. Issues with electrical circuit and PV modules themselves are the main internal issues. Within each category, there can be several sub-categories, reflecting root causes or prominent characteristics in a more refined manner. The possible IV curve patterns for selected categories are illustrated in Fig. 1.

It should be noted that:

- The IV curve symptoms for each category may not be unique. It is well possible for two or more issues to exhibit similar IV curve patterns. Multiple techniques can potentially be used to further distinguish similar patterns, for example by extracting the exact values of relevant parameters (Isc, Voc, slopes, inflexion point positions, etc). However, overdoing it will be fruitless in practice due to the complexity of operating conditions, inhomogeneity, measurement imperfection, lack of detailed information about modules and array configurations, and potential complication resulting from coexistence of issues. In reality, operators do not need a model that can single out a root cause to a very high accuracy. Narrowing down possible causes is very useful in guiding field inspection already.
- Shading is an important category that is sometimes difficult to confirm purely from performance data. Some shading events are non-actionable by nature. However, identifying these causes are still important for excluding shading episodes in further performance analysis steps and to rule out irrelevant performance alarms to avoid unnecessary O&M costs. In addition, it is desirable to understand what type shading event is taking place. For example, a shading type may be normal for rooftop systems but not for utility scale farms.
- Uniform effects (for example from homogeneous soiling or uniform shading) that do not cause significant change in the characteristic of IV curve shapes can be difficult to detect by mass IV curve scanning alone.
- Catastrophic electrical faults are not the main use case of this method. Timely detection with low latency is important for acute electrical faults for safety reasons. This would require real time high frequency sensing and detection from hardware themselves. The need is therefore different from performance management for O&M purposes, which typically involves monitoring resolution of at most 5-minute and only infrequent IV scanning.

TABLE I. UNDERPERFORMANCE/FAULT CATEGORIES FOR IV CURVE DIAGNOSIS

Category	Sub-category
Shading	Local slight shading
	Widespread slight shading
	Local near shading
	Widespread near shading
	Distributed/irregular shades
Surface coverage	Bird dropping / leaves / debris
	Melting snow
	Inhomogeneous soiling
	Bottom row soiling / dirt dam

Electrical issues	Excessive series resistance
	Electrical leakage (shunt)
	Shorted diodes
	Open diodes
	Hot spot
	Short-circuited cells
	Line-to-line fault
Module quality / degradation	Major cell/glass cracks
	Round knee
	PID
	Degraded junction
	Cell resistance issues

B. *Experiment setup*

In this work, several classes with distinctive IV curve patterns are chosen for a prove of concept study. Details about these classes are shown in Table 2. The IV curve patterns are of two broader types, shading/mismatch issues and resistance issues. For each class, extensive IV curve simulation is performed using analytical solar cell and string models. The possible parameter space considers array design, operating environment, electrical characteristics, and extent of issue. Plausible ranges for each parameter are defined for each scenario. Values are regularly sampled from a subset of the parameter space. The array design variation includes three parameters: portrait or landscape, number of modules per string, and number of rows spanned by each string. Irradiance level and temperature are varied for operating condition space. The varied electrical parameters include series resistance, shunt resistance, reverse saturation current, and number of cells in a module. For each scenario, a model is designed to mimic field behavior of a PV string under that scenario. For example, in shading scenarios, number of sub-strings shaded, amount of irradiance reduction within shaded areas, as well as distribution of shading extent are varied. With this simulation setup, a rich set of IV curves with labels can be generated.

TABLE II. IV CURVE CLASSES USED IN THE POC STUDY

Class code	Class label	Input parameters characteristics
0	Rseries issue	Increase Rseries to large value
1	Rshunt issue	Decrease Rshunt to small value
2	normal	Baseline assumptions
3	Series + shunt resistance	Simultaneously change Rseries and Rshunt
4	extensive near shading	Large fraction of string shaded; Very low irradiance for shaded part; Little variation (clean cut)
5	local near shading	Small fraction of string shaded; Very low irradiance for shaded part; Little variation (clean cut)
6	extensive slight shading/mismatch	Large fraction of string shaded; Not so low irradiance for shaded part; Various degrees of variation
7	local slight shading/mismatch	Small fraction of string shaded; Not so low irradiance for shaded part; Various degrees of variation
8	Distributed shade/soiling/mismatch	Small to large fraction of string shaded; Significant variation of shaded irradiance

The labeled IV curve data is then used to perform a supervised learning for a neural network architecture using 1D CNN and densely connected layers (Fig 2). The IV curves are normalized to their Isc and Voc, but otherwise do not require irradiance or temperature measurements to do correction as a preprocessing step. The training was optimized using the usual deep neural network tuning and hyperparameter search techniques.

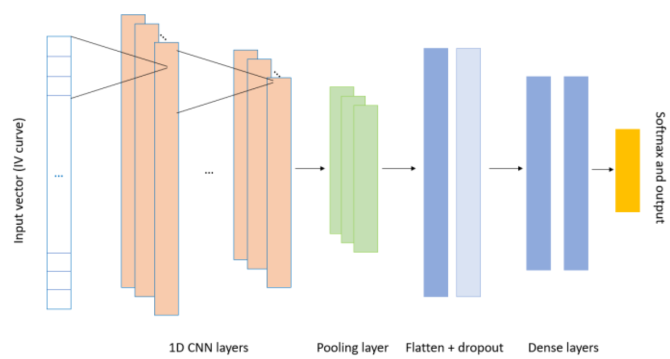

Fig 2. Network architecture used in this study.

To validate the trained model, a test set of IV curves is generated with values sampled from the parameter space differently from the training set. This is the ensure that the IV curves in the test set are sufficiently distinct from those in the training set. Therefore, the model performance on the test set can better reflect the model's generalization power and indicate overfitting.

III. Results and Discussions

The classification result by the optimized model on the test set is shown in a confusion matrix plot and ROC curves (Fig 3). The scores of precision, recall and F1-score are tabulated in Table 3. The model is able to classify the broad types of issues (shade/mismatch VS resistance issue) to a very high accuracy. Most notably, all the shading/mismatch classes have very high F1-score above 0.9. The model has relatively lower performance on distinguishing among normal and the various resistance issues. There are generally more false positives for resistance issues, leading to low precision. The IV curves for these classes are all smooth curves, varying only in the slopes of the horizontal and vertical legs. It is possible that a single neural network model with a fixed set of hyperparameters is not able to pick up both the smaller features of shading/mismatch behavior and the larger feature such as slopes. Fortunately, these classes are relatively easy to classify by simply calculating the slopes similar to the usual IV curve processing steps.

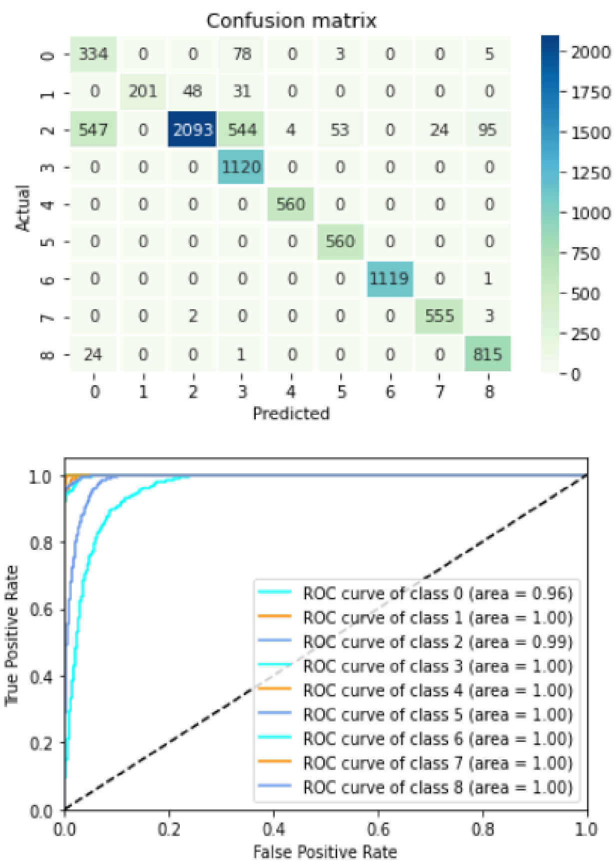

Fig 3. Confusion matrix and ROC plot of the optimized 1d CNN model on the test set.

TABLE III. SCORES OF THE OPTIMIZED 1D CNN MODEL ON THE TEST SET.

class	precision	recall	f1-score	support
0	0.37	0.8	0.5	420
1	1	0.72	0.84	280
2	0.98	0.62	0.76	3360
3	0.63	1	0.77	1120
4	0.99	1	1	560
5	0.91	1	0.95	560
6	1	1	1	1120
7	0.96	0.99	0.97	560
8	0.89	0.97	0.93	840
accuracy			0.83	8820

In comparison, the classification accuracy achieved on a validation set sampled from the training set is higher (Fig 4), which is expected. Nonetheless, it can be seen that the model still retained very good performance on the test set. Arguably, the model had succeeded to a large degree in extracting salient features of the IV curve patterns with the CNN layers instead of overfitted to the exact curves of the simulated configurations. Its performance is expected to be comparable to human judgment in the classification task using only IV curves themselves.

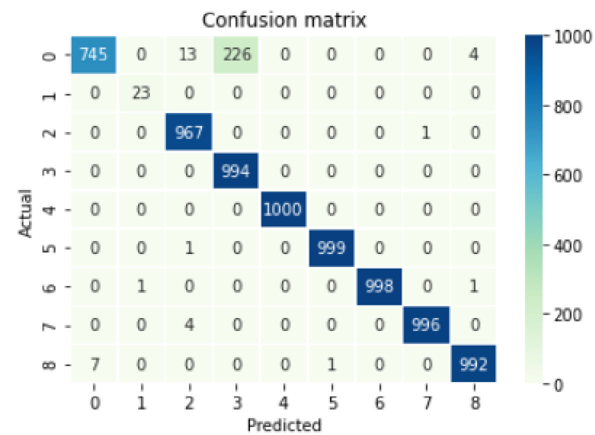

Fig 4. Confusion matrix plot of the optimized 1d CNN model on the training validation set.

To expand the model, it is possible to make use of extra information such as irradiance, temperature, and analytically extracted IV curve parameters as additional input nodes to append to the fully connected layers after the CNN layers. More importantly, the diagnosis result can be further enhanced downstream by corroborating with time series performance monitoring, advanced analytics results, cross comparison with nearby strings, or simply repeating the scan at different times. Such technique of "triangulation" would require a comprehensive monitoring platform to onboard and relate various source of information as a holistic solution.

IV. CONCLUSIONS

IV curve scanning is becoming an important technique for managing the performance of solar assets. It helps to understand the PV system condition and pinpoint potential health issues, which is greatly beneficial for a more efficient O&M. Using a novel framework of underperformance/fault allocation and deep learning classification engine, we demonstrate the possibility to automatically and accurately detect issues that may be present in the field to guide targeted field inspection and rectification work. The proposed categories for IV curve diagnosis are broad spectrum, including various types of shading, surface coverage, electrical issues, and module quality/degradation.

Using our in-house simulated IV curve library, a deep learning model utilizing 1D CNN and densely connected layers are trained with large volume of data. The model can classify different types of shading and resistance issues to a high accuracy. The model can detect irregular patterns within the IV curve, giving rise to powerful detection and allocation of shading scenarios. The precision for identifying resistance issues is lower in comparison, but this can be fixed by additional feature engineering.

The flexibility to expand the model by taking in more input information and the potential to adapt to field data using transfer learning is another important advantage of this approach. Furthermore, the diagnosis results can be improved downstream by making use of performance data and other analytics results. This technique of triangulation using various sources of data requires strong capability of the monitoring platform to onboard and relate multiple sources of information as a holistic solution. This technique is being tested under the infrastructure of Envision's AIoT platform EnOS™ and its advanced analytics software Ensight™.

ACKNOWLEDGMENT

This research is supported by Envision Digital International Solar Center of Excellence. Envision Digital is a global AIoT technology provider headquartered in Singapore. With the world-class AIoT operating system EnOS™, as well as monitoring, advanced analytics, forecasting and optimizing applications, Envision provides services to enable digital transformation, especially in the renewable energy sector.

REFERENCES

[1] S. Sarikh, M. Raoufi, A. Bennouna, and B. Ikken, "Characteristic curve diagnosis based on fuzzy classification for a reliable photovoltaic fault monitoring," Sustain. Energy Technol. Assessments, vol. 43, no. May 2020, p. 100958, 2021, doi: 10.1016/j.seta.2020.100958.

[2] B. Li, A. Migan-Dubois, C. Delpha, and D. Diallo, "Evaluation and improvement of IEC 60891 correction methods for I-V curves of defective photovoltaic panels," Sol. Energy, vol. 216, no. August 2020, pp. 225–237, 2021, doi: 10.1016/j.solener.2021.01.010.

[3] C. Li, Y. Yang, K. Zhang, C. Zhu, and H. Wei, "A fast MPPT-based anomaly detection and accurate fault diagnosis technique for PV arrays," Energy Convers. Manag., vol. 234, no. August 2020, p. 113950, 2021, doi: 10.1016/j.enconman.2021.113950.

[4] D. Wei, M. Wei, H. Cai, X. Zhang, and L. Chen, "Parameters extraction method of PV model based on key points of I-V curve," Energy Convers. Manag., vol. 209, no. November 2019, p. 112656, 2020, doi: 10.1016/j.enconman.2020.112656.

[5] J. M. Huang, R. J. Wai, and W. Gao, "Newly-designed fault diagnostic method for solar photovoltaic generation system based on IV-Curve measurement," IEEE Access, vol. 7, pp. 70919–70932, 2019, doi: 10.1109/ACCESS.2019.2919337.

[6] S. Fadhel et al., "PV shading fault detection and classification based on I-V curve using principal component analysis: Application to isolated PV system," Sol. Energy, vol. 179, no. June 2018, pp. 1–10, 2019, doi: 10.1016/j.solener.2018.12.048.

[7] S. Sarikh, M. Raoufi, A. Bennouna, A. Benlarabi, and B. Ikken, "Fault diagnosis in a photovoltaic system through I-V characteristics analysis," 2018 9th Int. Renew. Energy Congr. IREC 2018, no. Irec, pp. 1–6, 2018, doi: 10.1109/IREC.2018.8362572.