HYBRID DEEP LEARNING MODEL FOR BYPASS DIODE FAULTS IN PHOTOVOLTAIC SYSTEMS

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ABSTRACT
The reliability, efficiency, and maintenance of photovoltaic (PV) systems have become increasingly critical as installed capacity increases. Faults in PV arrays not only lead to production losses but also pose serious safety risks, including hot-spot formation, module degradation, and fire risk. Especially, open-circuit or short-circuit faults in bypass diodes, which serve as the module's protection mechanism, cause permanent damage and efficiency losses by disrupting the module's electrical characteristics. Therefore, early detection and accurate classification of bypass diode faults are fundamental requirements for the sustainability of PV panels. This study proposes to classify the effects of bypass diode failures in PV panels on the fundamental current-voltage and power-voltage characteristics. Different operating conditions and failure scenarios were modelled in MATLAB/Simulink, and a dataset was generated from the resulting data. Using the created dataset, a hybrid deep learning model based on 1DCNN- BiLSTM was developed. The model's performance was evaluated. The results demonstrate that the proposed approach can effectively distinguish bypass diode failures. The model developed in this study aims to contribute to early failure detection and increased reliability in PV systems.
Keywords: Bypass diode faults, 1D-CNN, BiLSTM, Photovoltaic systems.

INTRODUCTION

As the installed capacity of photovoltaic (PV) systems increases, the reliability, efficiency, and maintenance processes of these systems have become critically important. Failures in PV arrays not only lead to production losses but can also pose serious safety risks, including hot-spot formation, module degradation, and fire risk (Aghaei et al., 2022; Koester et al., 2022).

Bypass diodes are protective devices designed to reduce module losses during reverse-bias operation by allowing current from functional cells to bypass defective cells. When a significant disparity in short-circuit current exists among multiple cells, the cell or cells with the lowest current may become reverse-biased and subsequently overheat. This may occur temporarily during shading or permanently if a cell or the internal electrical circuit is damaged (Aghaei et al., 2022). Open-circuit or short-circuit faults in bypass diodes, which serve as the module's protection mechanism, cause permanent damage and efficiency losses by disrupting the module's electrical characteristics (Dhimish & Chen, 2019). Therefore, early detection and accurate classification of bypass diode faults are essential for the sustainability of PV systems.

Conventional fault detection techniques typically rely on linear behavior or particular threshold levels. However, under environmental conditions such as aging, temperature, shade, and irradiance, the I-V characteristics of PV systems exhibit a complex, non-linear structure (Liu & Wu, 2025). Because of this, conventional approaches are insufficient in situations with changing conditions and noisy data. Deep learning-based approaches have come to the fore in recent years to overcome these challenges. Deep learning (DL) is a powerful tool that can extract features from raw data through its multi-layered architecture. DL algorithms have achieved high success rates in detecting faults in time-series electrical signals, particularly in PV fault detection.

The models used in this study offer different data processing capabilities. A One-Dimensional Convolutional Neural Network (1DCNN) is particularly effective at capturing local changes, breakpoints,

and curve formations in time series data via filters. Bidirectional Long Short-Term Memory (BiLSTM) networks, unlike standard Recurrent Neural Networks (RNNs), can learn long-term dependencies and process data in both forward and backward directions, enabling them to model temporal relationships more robustly. The hybrid use of these models plays a complementary role in solving the structure of PV bypass diode failures.

DL models are becoming increasingly common for detecting PV system faults. Aljafari et al. proposed a 1D CNN-based approach for fault detection in grid-connected PV systems, achieving high accuracy (Aljafari et al., 2024). Similarly, Gao and Wai developed a hybrid model that combines a CNN and a GRU to identify faults in PV series (Gao & Wai, 2020). Chen et al. presented a method for diagnosing PV array failures using deep residual networks with I-V curves (Chen et al., 2019). Dhimish and Chen, on the other hand, have conducted research on detecting bypass diode failures using artificial neural networks. However, they have demonstrated that more advanced models are needed for complex shadowing scenarios (Dhimish & Tyrrell, 2023).

In this study, a hybrid DL model incorporating 1DCNN and BiLSTM has been developed for the detection and classification of bypass diode faults in PV panels. Within the scope of the study, the LEXRON LXR-80-36 model solar panel was modeled in MATLAB/Simulink. Six scenarios, including open-circuit and short-circuit bypass diode faults and partial shading conditions, were modeled. The obtained I-V and P-V data were processed using the proposed structure.

The developed hybrid model was found to classify six different fault classes with 98.2% accuracy. No signs of overfitting were observed in the training and validation loss plots, and the model showed a stable, robust structure. 5-fold validation was applied to confirm the performance metrics. The findings reveal that the combination of 1DCNN's feature extraction power and BiLSTM's temporal correlation capability provides an advantage in diagnosing complex PV faults.

2. BYPASS DIODE FAULT DETECTION WITH DATA-DRIVEN METHODS

PV system behavior exhibits a nonlinear, complex structure due to environmental factors. This complex structure can cause classical threshold-based methods to produce false alarms and low accuracy. An effective fault detection mechanism is crucial for reducing maintenance costs, enhancing system security, and ensuring energy continuity.

PV system faults are categorized into two main groups according to the originating parameter: those originating from the PV generator side (modules, strings, cabling, and connections) and those originating from balance-of-system components (inverters, protection equipment, and AC side). Additionally, faults are classified as electrical faults (open circuit, short circuit, phase-to-phase faults, mismatch), defect-based faults (cell cracking, delamination, corrosion, PID), and temporary effects due to environmental conditions (partial shading, dust accumulation, temperature-induced deviations) (Aarseth et al., 2022).

Electrical faults in PV modules rarely occur as single-point failures. Instead, they manifest as inconsistencies arising from certain cell groups within the module operating differently from others. Partial shading, contamination, cell cracks, or local temperature differences can alter the module's I–V and P–V characteristics (Aarseth et al., 2022).

Under partial shading conditions, bypass diodes are activated to protect cell groups that remain reverse-biased and to limit power loss. However, if the bypass diode fails (open circuit or short circuit), the current and voltage behavior under shading is disrupted, and power loss increases. This creates a critical problem for both performance and fault diagnosis. In this context, bypass diode failures should be considered not only as the failure of a single component but also as a failure class that increases the risk of other failures when the module's protection mechanism is disabled or malfunctions.

DL is a learning approach that can automatically extract distinctive features from raw data and represent complex patterns thanks to multi-layered structures. The main reason DL stands out in PV fault detection is that it can learn the non-linear effects of different fault types in electrical signals or image-based data,

with less need for feature design.

A common method in PV fault classification is to combine CNNs' local pattern extraction with the ability of structures such as LSTM and GRU to model sequential data. For example, in PV sequence fault diagnosis, studies combining CNN-based feature extraction with sequential units have shown higher discrimination success than solutions based on a single model family (Taghezouit et al., 2024).

3. BYPASS DIODE FAULTS CLASSIFICATION WITH HYBRID DEEP LEARNING MODEL

In this study, the LEXRON LXR-80-36 model solar panel was modeled in Simulink, and its behavior under different bypass diode failure scenarios was investigated. The panel consists of 36 PV cells connected in series, with one bypass diode connected in reverse parallel to each 12-cell subarray. During modeling, a separate Solar Cell block was used for each cell in MATLAB/Simulink. The nominal operating values of the PV panel are shown in Table 1. In this model, the I-V (current-voltage) and P-V (power-voltage) characteristics of the panel were obtained under different irradiance and temperature conditions. In the simulations, Standard Test Condition was used (1000 W/m² irradiance, 25°C temperature, and 1.5 AM).

Table 1. The electrical properties of the PV panel

Maximum Power (Pmax)	80 W	**Maximum Power Current (Imp)**	4.44 A
Open Circuit Voltage (Voc)	22.10 V	**Total Number of Cells**	36
Maximum Power Voltage (Vmp)	18.00 V	**Number of Bypass Diodes**	3
Short Circuit Current (Isc)	4.86 A		

PV panel behavior was examined under both normal operation and bypass diode failure conditions. The required dataset was generated from current, voltage, and power parameters across six operating scenarios, as shown in Table 2. Simulation studies cover not only normal operating conditions but also short-circuit, open-circuit, and multiple fault conditions. The dynamic behavior of these cases under partial shading was also analyzed to test the model's distinctive performance.

Table 2. Fault scenarios with open-circuit and short-circuits with and without shading.

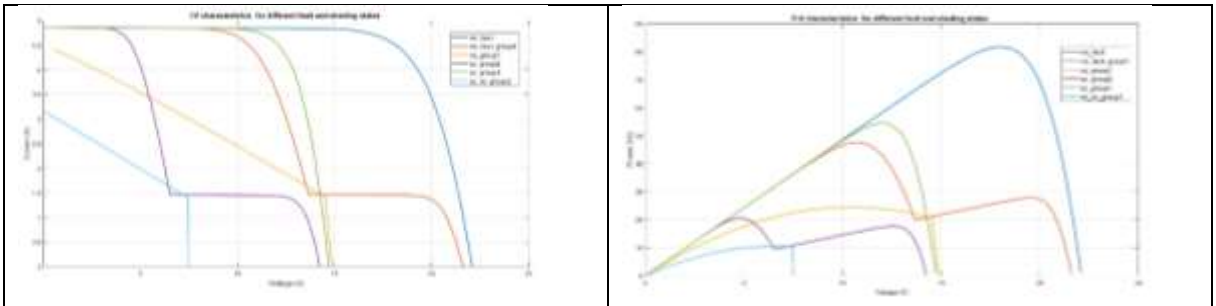
CLASS NAME	FAULT CONDITION	SHADING CONDITION
no_fault	There are no faults in the bypass diodes.	No shading.
no_fault_group1	There are no faults in the bypass diodes.	The first group is shaded.
oc_group1	The first bypass diode has an open-circuit fault.	The first group is shaded.
sc_group2	The first bypass diode has a short-circuit fault.	The second group is shaded.
sc_group1	The first bypass diode has a short-circuit fault.	The first group is shaded.
sc_ad_group2	The first bypass diode has a short-circuit fault, and the second bypass diode has an open-circuit fault.	The second group is shaded.

The outputs of the implemented scenarios were based on current, voltage, and power values. The scenarios included no fault, short-circuit bypass diode fault, open-circuit bypass diode fault, both faults occurring simultaneously, and the behavior of these scenarios under partial shading.

The proposed model begins by processing the three-channel PV data using sequential Conv1D layers. In the first stage, local features on the I–V and P–V curves are extracted using 64 and 128-filter convolutional blocks. Following each convolutional layer, Batch Normalization and MaxPooling1D operations are applied to stabilize the feature maps and reduce their dimensions. The obtained features are passed to a BiLSTM layer, which analyzes sequential dependencies in both directions. After the BiLSTM output is regularized with Dropout, it is projected onto a more compact representation space via two fully connected (Dense) layers, and classification is performed in the final layer for six different operating conditions.

4. RESULTS AND DISCUSSION

The I–V and P–V characteristics from the proposed simulation model in Figures 1(a) and 1(b) were comparatively analyzed under different shading and bypass diode failure scenarios, as shown in Table 2.

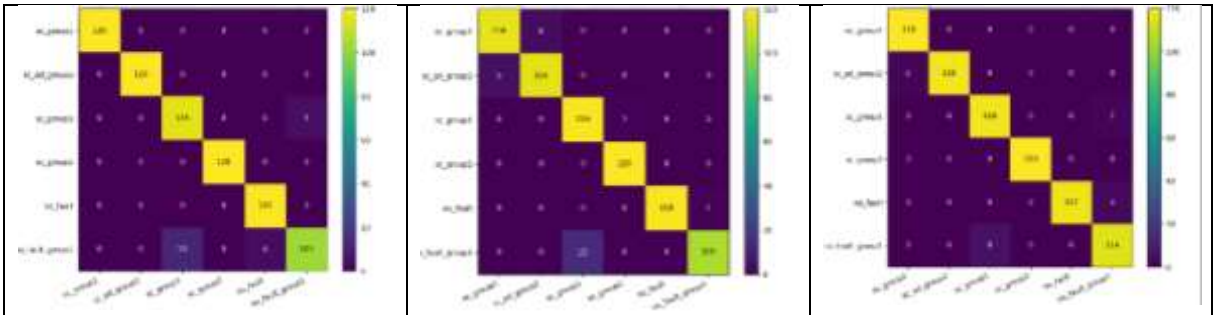


(a) I-V characteristics (b) P-V characteristics

Figure 1. Electrical characteristics of a PV panel under various bypass diode fault conditions and partial shading scenarios.

The blue no_fault curve is for the healthy operating condition, with $V_{oc} \approx 22\,V$ and $I_{sc} \approx 4.48\,A$ values matching the panel's nominal characteristics. The maximum power point on the P–V curve is approximately 80 W The red no_fault_group1 curve shows that a substring was shaded, causing the bypass diode to conduct and resulting in a distinct step-like voltage drop in the I–V curve. Due to the presence of three bypass diodes in the panel, disconnecting one substring reduced the voltage by approximately one-third, and the V_{oc} value dropped to approximately $14 - 15\,V$. This is consistent with theoretical expectations. In the green (sc_group1) and purple (sc_group2) curves, it was observed that the voltage remained permanently low across the entire current range, and the maximum power value decreased significantly due to a short-circuit bypass diode failure. In the yellow oc_group1 curve, the voltage exhibits a sharp, linear decline toward zero as the current increases, which is a characteristic signature of an open-circuit bypass diode failure under shading. This behavior results in a significant reduction in the area of the P-V curve. Similarly, the light blue sc_oc_group2 curve shows a combined effect, starting at a low initial voltage and rapidly decreasing toward the origin, indicating a mixed-failure condition. The results exhibit physical behavior consistent with the panel parameters and diode theory, showing that each fault scenario produces distinguishable characteristic signatures for the deep learning model. The analysis is specifically focused on the active power generation region ($0 \leq V \leq V_{oc}$), as this range represents the practical operational window of typical PV inverters and MPPT controllers.

To validate the effectiveness of the proposed hybrid model, the classification performance of the 1DCNN, BiLSTM, and Hybrid 1DCNN-BiLSTM models was compared using confusion matrices. When examining the confusion matrices provided in Figure 2, it is observed that the models largely classify correctly and that predictions are concentrated on the diagonal. In particular, error-free or near-error-free results have been obtained in the ad_group1, sc_group2, and no_fault classes. Additionally, it was observed that the 1DCNN model is good at in instantaneous signal changes, while the BiLSTM model excels in temporal dependencies. The proposed hybrid 1DCNN-BiLSTM model combines the advantages of both architectures, achieving the highest accuracy across all fault classes. The diagonal concentration in the confusion matrices demonstrates that the model can distinguish between complex fault signatures that are particularly similar to each other (open and short-circuit scenarios) with nearly 100% accuracy.



(a) 1DCNN (b) BiLSTM (c) Hybrid 1DCNN BiLSTM

Figure 2. Confusion matrices for the ablation study.

Figure 3 shows the accuracy and loss plots for the hybrid model. The model's training and validation curves converged with high stability within approximately 10 epochs. The accuracy rate exceeding 99% and the loss approaching zero demonstrate that the hybrid structure has achieved excellent generalization capability without overfitting.

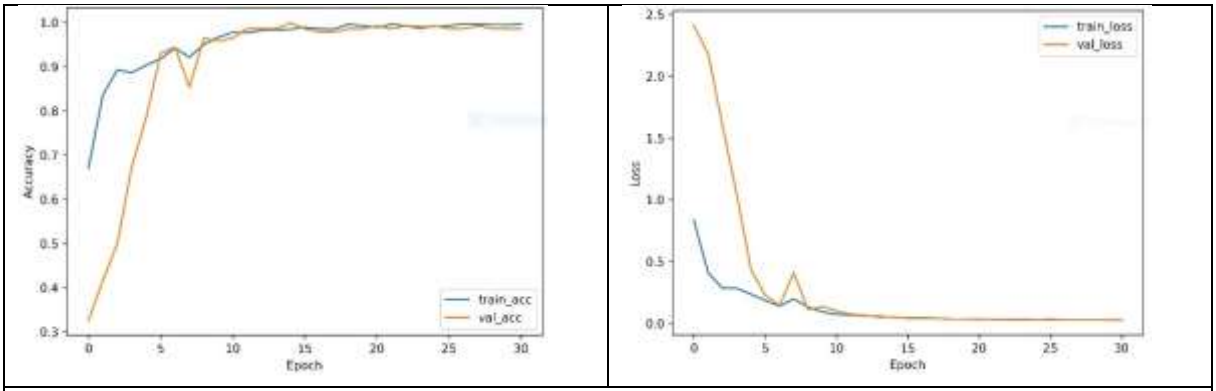


Figure 3. Training and validation performance of the proposed hybrid model.

Table 3 shows that the 1DCNN-BiLSTM hybrid model outperforms the individual models across all performance metrics (Accuracy, Precision, Recall, and F1-Score). In particular, the values of 98.2% accuracy and 98.3% F1-Score demonstrate that the model achieves high diagnostic sensitivity by combining both instantaneous signal features and temporal dependencies. The similar performance of the 1DCNN and BiLSTM models (96.9% and 96.4%) confirms that both features are critical for fault detection; however, the highest success is achieved by combining these two structures.

Table 3. Performance metrics for detecting PV panel bypass diode faults with deep learning.

Model	Accuracy	Precision	Recall	F1-Score
1DCNN	96.9%	96.0%	97.0%	96.6%
BiLSTM	96.4%	95.0%	96.0%	95.7%
1DCNN-BiLSTM	98.2%	98.5%	98.2%	98.3%

To test the model's generalization ability, 5-fold cross-validation was used, as seen in Table 4. The results confirm that the proposed hybrid model delivers consistent performance. The average success rate exceeds 98% and, in particular, the accuracy of 0.9931 achieved in the final folds demonstrates that the model maintains high accuracy across different data subsets.

Table 4. 5-fold cross-validation results for the hybrid 1DCNN-BiLSTM architecture.

Fold	Accuracy	Precision	Recall	F1-Score
1	0.9583	0.9605	0.9583	0.9583
2	0.9722	0.9722	0.9722	0.9722
3	0.9931	0.9933	0.9931	0.9931

4	0.9931	0.9933	0.9931	0.9931
5	0.9931	0.9933	0.9931	0.9931
Mean, Std. Dev	98.20% ±0.0155	98.25% ±0.0147	98.20% ±0.0155	98.20% ±0.0155

5. CONCLUSION

In this study, the effects of bypass diode faults on the fundamental current-voltage and power-voltage characteristics of PV panels are investigated. As a result of ablation studies, the highest Accuracy and F1-score (Macro) values were achieved with the 1DCNN-BiLSTM architecture compared to 1DCNN and BiLSTM models. The CNN layer successfully learned local features, while the BiLSTM layer successfully learned temporal dependencies; this combination provided a significant performance improvement over the individual models. The results obtained demonstrate that the proposed approach is an effective method for the reliable and balanced detection of bypass diode failures.

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