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A multi-scale dual-stage model for PV array fault detection, classification, and monitoring technique

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ABSTRACT

The output generated by photovoltaic arrays is influenced mainly by the irradiance, which has non-uniform distribution in a day. This has resulted in the current-limiting nature and nonlinear output characteristics, and conventional protection devices cannot detect and clean faults appropriately. This paper proposes a low-cost model for a multi-scale dual-stage photovoltaic fault detection, classification, and monitoring technique developed through MATLAB/Simulink. The main contribution of this paper is that it can detect multiple common faults, be applied on multi-scale photovoltaic arrays regardless of environmental conditions, and be beneficial for photovoltaic system maintenance work. The experimental results show that the developed algorithm using supervised learning algorithms mutual with k-fold cross-validation has produced good performances in identifying six common faults of photovoltaic arrays, achieved 100% accuracy in fault detection, and achieved good accuracy in fault classification. Challenges and suggestions for future research direction are also suggested in this paper. Overall, this study shall provide researchers and policymakers with a valuable reference for developing photovoltaic system fault detection and monitoring techniques for better feasibility, safety, and energy sustainability.

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1. INTRODUCTION

Globally, power generation from solar photovoltaic (PV) systems is experiencing a significant increase [1]. This increase has also led to risks associated with damage to PV system components, injury to operators, and fire hazards to PV systems and buildings. Since PV output is nonlinear, conventional protection devices (CPD) such as fuses and circuit breakers can detect faults and isolate faulty circuits only at large fault currents and voltages. Therefore, better fault detection and monitoring techniques for PV systems are needed [2] for better feasibility, safety, and energy sustainability. Recent studies have developed advanced or intelligent fault detection and monitoring techniques for solar PV systems. The main ones are model-based and IV power loss curve approaches, machine learning techniques, statistics-based techniques, and output signal analysis techniques [3].

The model-based approach for detecting and identifying PV faults compares the expected data obtained from the simulation process with data measured from an experiment or data collected from a PV system [4]–[7]. This technique involves the least integration complexity with PV systems and requires low implementation costs. However, most studies have found that the accuracy obtained is lower than other advanced PV fault detection methods. Machine learning (ML) techniques, on the other hand, have been the most favorable method for detecting and diagnosing PV systems faults. This approach exploits artificial intelligence with three main algorithms; supervised learning, semi-supervised learning, and unsupervised learning in task completion [8]–[15]. Studies have proven this technique acquires high accuracy. Still, the need for data acquisition systems and advanced computing system skills has made it complex and challenging to integrate with PV systems and expensive to implement.

Meanwhile, statistical-based analysis mostly sets a threshold value and compares it with the actual value measured in determining a PV system's normal or faulty state [13]–[16]. Earlier studies indicated that approaches using mean differences or variances have better abilities in determining errors in the PV system. Though, incorrectly setting the threshold limit can reduce method accurateness. Lastly, the output signal analysis using the frequency-time domain to detect abnormalities in the sample in identifying faults in the PV system has also attained high accuracies [17]–[20]. Nevertheless, it requires sophisticated tools to generate the signal and making it the most expensive method.

Furthermore, most of the methods/techniques that have been developed in the previous study were only to detect specific faults and did not provide fault location. Whereas finding the location of the fault is always challenging and time-consuming for large-scale PV systems [21], [22]. Apart from developing previous fault detection methods mostly only tested or evaluated on small-scale PV arrays/systems, they did not examine the PV fault detection methods on the maintenance aspects. Studies have found a good maintenance system is important for inspecting and performing corrective work because different incidents or failures have different characteristics that require specialized competent people, different tools and techniques to deal with and implement corrections [23].

Hence, in this paper, we developed the multi-scale dual-stage (MsDs) model for PV fault detection, classification, and monitoring technique, which requires a low implementation cost, can detect multiple faults with fault locations, and can be applied to all PV array scales, also useful for PV maintenance works. The dual-stage algorithm comprises of fault detection algorithm at stage-1 and fault classification and location at stage-2. The MsDs has employed supervised learning techniques of discriminate analysis (DA), k-nearest neighbor (KNN), support vector machine (SVM), random forest (RF) in identifying the best algorithm which produces the best accuracy.

The remaining part of this paper is organized as follows: i) Section 2 describes PV array modeling and simulation processes; ii) After that, section 3 presents the proposed MsDs technique; iii) Then, section 4 provides the simulation and testing algorithm's results, discussion, and limitations; and iv) Finally, section 5 presents the conclusion and recommendation for future work direction.

2. PV ARRAY MODELING AND SIMULATION

2.1. Model and input data for solar cells

A one-diode model (ODM) is chosen in the study to develop PV array modeling because of its advantages compared to the double-diode model. It has good accuracy for steady-state conditions and faults analysis for PV systems. Further, ODM parameters for PV modules are available for most PV modules in the market and are the most commonly chosen model by researchers [24]. The equivalent circuit for ODM and its parameter is shown in Figure 1.

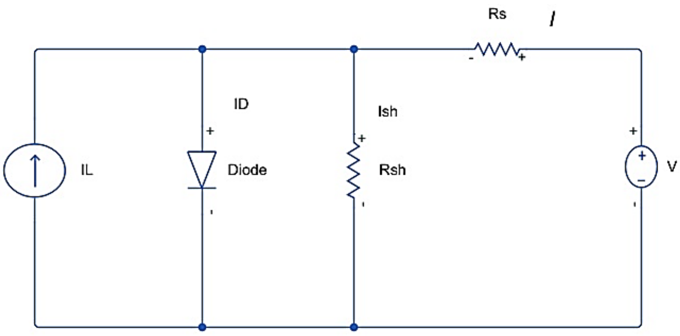


Figure 1. An equivalent circuit of a one-diode model with five parameters

By using Kirchhoff's law, the output current I in (A) of the PV cell is formulated as given by (1), (2), and (3), where the I_L represents light-generated current, while the I_D represents the diode current and I_{sh} represents the shunt resistance current.

$$I = I_L - I_D - I_{sh} \tag{1}$$

$$I_D = \exp\left(\frac{V+IRs}{AkT}.q\right) - 1 \tag{2}$$

$$I_{sh} = \frac{V+IRs}{Rsh} \tag{3}$$

Where q is the electron charge (1.6310^{-19} C), A is the diode ideal factor, T is the ambient temperature (K), V is the solar cell voltage, and k is the boltzmann's constant (1.38 310^{-23} J/K), the polycrystalline silicon PV modules model solartech energy ASC-6P-48-200 is taken for practical comparison. The value of input parameters of open-circuit voltage (Voc), short-circuits current (Isc), series resistance (Rs), and shunt resistance (Rsh) is obtained from the PV manufacturer's datasheet as in Table 1.

Table 1. Solartech energy ASC-6P-48-200 PV module parameters data

Parameter	Symbol	Value
Maximum Power	Pmpp	199.998 W
Open Circuit Voltage	Voc	30.12 V
Maximum Power Voltage	Vmp	24.6 V
Short Circuit Current	Isc	8.63 A
Maximum Power Current	Impp	8.13 A
Light-generated current	IL	8.6789 A
Diode saturation current	Io	2.929 x 10^{-10} A
Diode ideality factor	N	1.0136
Shunt resistance	Rsh	210.82 Ω
Series resistance	Rs	0.223 Ω
I_{SC} Temperature coefficient	α	0.06
V_{OC} Temperature coefficient	β	-0.35999
Solar cell number in series	n	48

2.2. Simulation procedure using MATLAB/Simulink

Modeling, simulation process, and development of PV array fault detection and classification algorithm are by using MATLAB/Simulink. Using simulation data can produce a more precise algorithm. In addition, it is useful for an unavoidable restriction in pandemic situations and the inevitable constraints with the impossibility of external operational irradiation to obtain data from the actual working conditions of the PV system. Six common faults or abnormal conditions of PV array, namely, degradation array (DF), open-circuit fault (OCF), line-line fault (LLF), ground fault (GF), partial shading (PS) condition, and faulty module (FM), were explored respectively in this study. A PV module consists of several solar cells with identical parameters, as shown in Figure 2. Several PV modules/panels were then used to build PV arrays, a modified version adopted in [8]. In this study, the small-scale PV array model was configured as five parallel PV strings of six in a series (5*6) of PV modules, as presented in Figure 3.

The simulation process assumed PV array is the only source of the fault current, and there is no overcurrent or overvoltage from external sources. A Simulink model of the I-V testing circuit configured was to generate the I-V curves and simulated data (power, voltage, and current) from the PV array models, as presented in Figure 4. This paper does not present PV array models for the six common fault simulations individually to save space. The models are combined on one diagram for description, as shown in Figure 5.

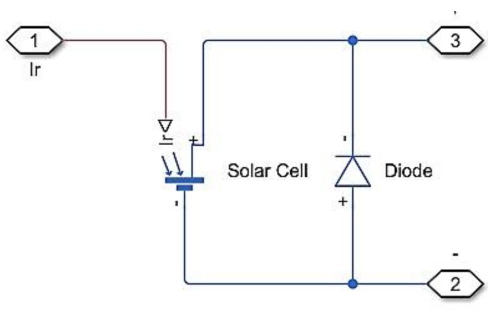


Figure 2. MATLAB/Simulink of the one-diode model module with solar cell

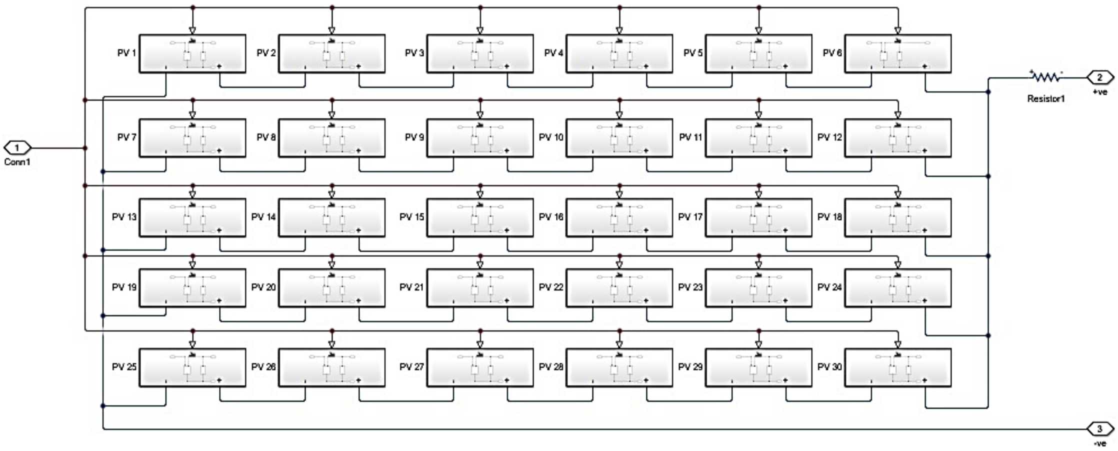


Figure 3. MATLAB/Simulink of 5*6 small-scale PV array model

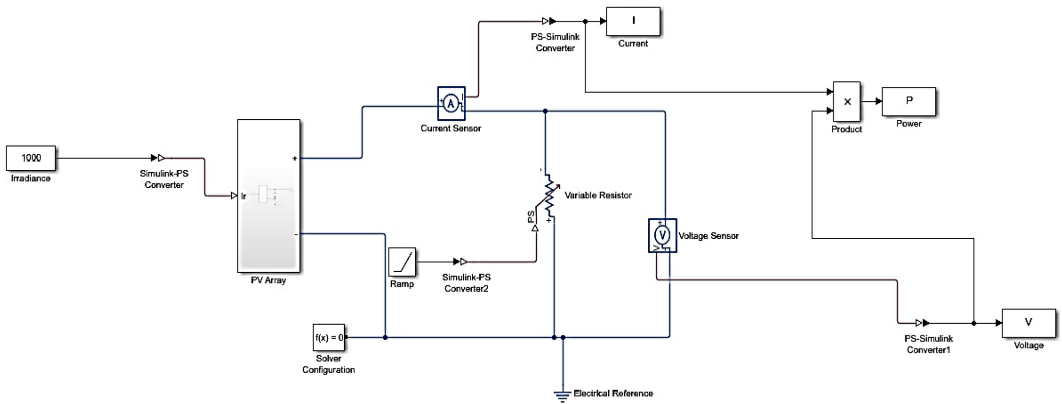


Figure 4. I-V characteristics circuit in MATLAB/Simulink

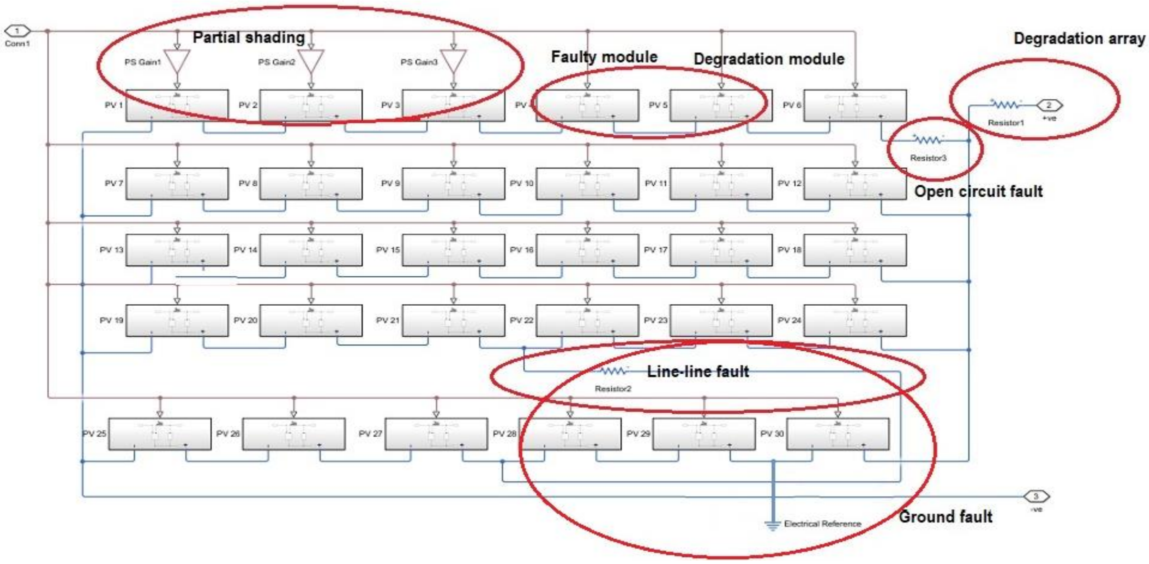


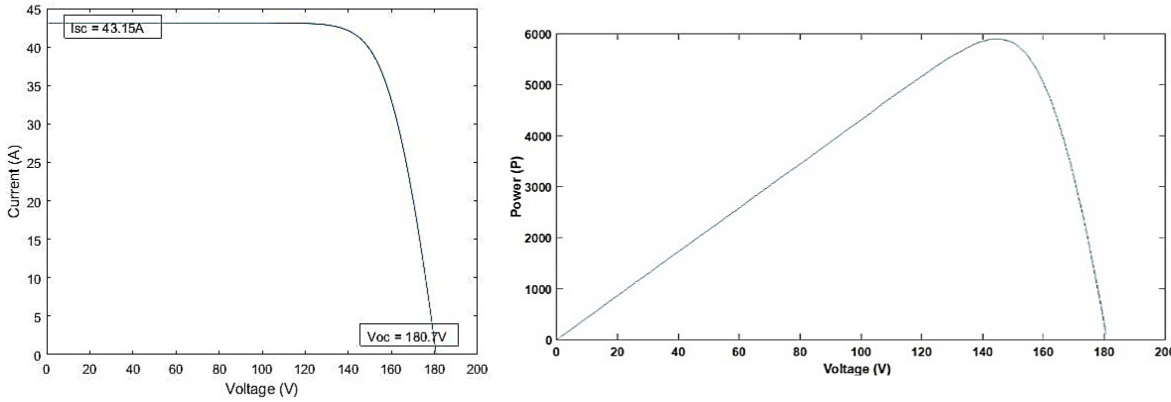
Figure 5. Description of six PV array faults simulation model

These six PV array fault models were simulated and tested under standard test conditions (STC) with radiation at 1000 W/m^2 and a module temperature of 25 ºC. The simulation processes were carried out as:

i) Simulation of the LLF model was performed by short-circuiting two different potential points in the PV array string. This simulation assumes that the fault impedance is zero, and the LLF at a large voltage difference fault was considered.
ii) Simulation of the GF model was achieved by extending the LLF model by connecting to the ground to create a fault current.
iii) Simulation of the PS model was carried out by setting PS Gain connected to PV modules to less than 1 to reduce the irradiance value received by the module(s) to less than 1000 W/m^2.
iv) Simulation of the OCF model was performed by adding an Rs to a PV array string, and Rs was set to infinity.
v) Simulation of the FM model was accomplished by reversing the bypass diode of the solar cell.
vi) Simulation of the DF model was performed by adding Rs to the PV array and gradually increasing the value of Rs.

2.3. PV array model validation

Figures 6(a) and 6(b) show the I-V and P-V curves generated from the simulation process under STC for a small-scale (5*6) PV array model. The developed PV array model was validated by comparing the simulation results of maximum power (Pmax), Voc, and Isc with the PV module manufacturer's datasheet available in the market. This study chose solartech energy ASC-6P-48-200 PV module.



(a) (b)

Figure 6. Simulation process of (a) I-V curve of PV array model and (b) P-V curve of PV array model

It can be seen that the simulation results are closely matched with the datasheet, as shown in Table 2. Therefore, this can be concluded that the proposed PV array model is accurate enough to predict the performance of the PV array under normal and fault conditions in this study.

Table 2. Comparison of simulation results (small-scale PV model) with actual PV module datasheet

Parameters	Solartech Energy ASC-6P-48-200		Simulated Data	
	Value of one module	Total of 5*6 PV array model	Value of one module	Total of 5*6 PV array model
Pmax	199.988 W	5999.94 W	200 W	6000 W
Voc	30.12 V	180.72 V	30.12 V	180.72 V
Isc	8.63 A	43.15 A	8.63 A	43.15 A

3. MULTI-SCALE DUAL-STAGE FAULT DETECTION AND CLASSIFICATION ALGORITHM

3.1. Medium-scale and big-scale PV array model: modeling and simulation

Medium-scale and big-scale PV array models were constructed through MATLAB/Simulink by adding panels in series and parallel strings, as shown in Figures 7 and 8. The data for input parameters; Voc, Isc, Rs, and Rsh for the medium-scale and big-scale PV array models were also from the PV manufacturer's datasheet, model solartech energy ASC-6P-48-200, as listed in Table 1. While, the simulation results of the medium-scale and big-scale PV array models under STC is presented in Table 3.

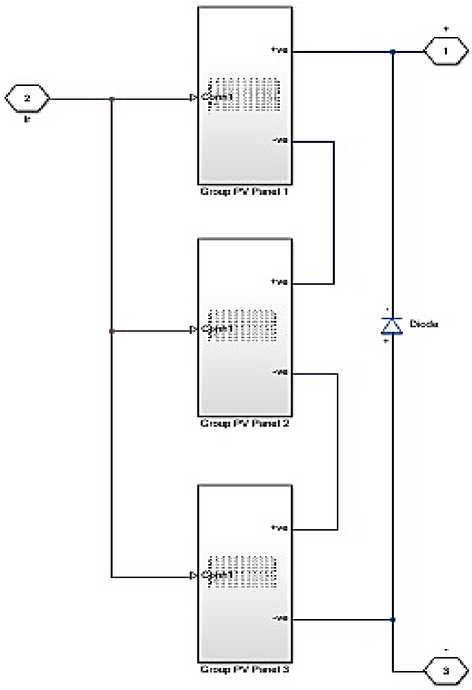


Figure 7. Model of medium-scale (10*30) PV array

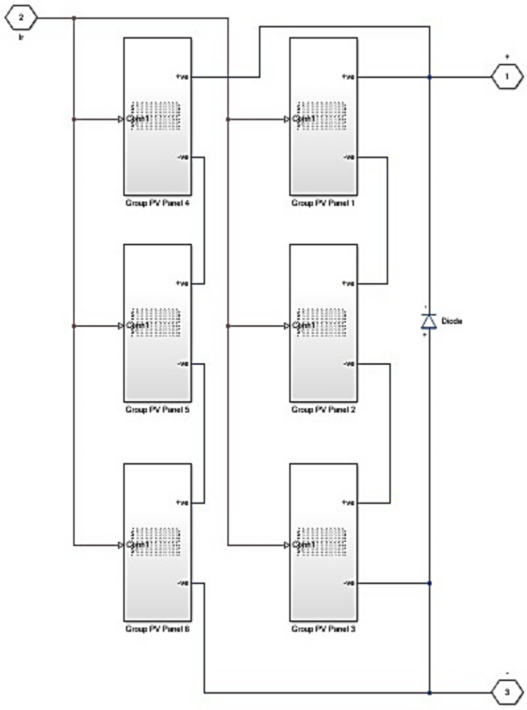


Figure 8. Model of big-scale (20*30) PV array

Table 3. Comparison of simulation results (medium-scale and big-scale PV model) with actual PV module datasheet

Parameters	Solartech Energy ASC-6P-48-200			Simulated Data of PV array model	
	Value of one module	Total of (10*30) module	Total of (20*30) module	Medium-scale (10*30)	Big-scale (20*30)
Pmax	199.99 W	59.99 kW	119.99 kW	60 kW	120 kW
Voc	30.12 V	903.7 V	903.7 V	903.7 V	903.7 V
Isc	8.63 A	86.3 A	172.6 A	86.3 A	172.6 A

It can be seen that the value of Pmax, Voc, and Isc generated are almost the same as the datasheet of solartech energy model ASC-6P-48-200, listed in Table 1. Hence, it can be concluded that the proposed medium-scale and large-scale PV array models are precise enough to predict their performance under normal and fault conditions in this study. The rest of simulation processes for medium and large-scale PV array fault models (LLF, GF, PS, OCF, FM, and DF) were carried out with the same procedure as the small-scale PV array model.

3.2. Fault detection and classification algorithm procedures

Figures 9(a) and 9(b) show the flowchart of the multi-scale dual-stage (MsDs) PV fault detection, classification, and monitoring technique procedures. The MsDs procedure consists of stage-1 and stage-2. A $(PV\_nofault)$ represents the PV array no-fault model, and (PV_fault^{n}) represents the PV array fault models of DF, FM, GF, LLF, OCF, and PS. The flowchart of stage-1 describes the fault detection algorithm. Due to the non-uniform PV output characteristics, a simple PV fault detection algorithm has been developed to compare power, voltage, and current generated from the PV array fault-free model, which is higher than the PV array fault model [25].

The parameter chosen for the testing of the detection algorithm is a difference in open-circuit voltage (RVoc), a standard deviation of output power (stdP), and mean output voltage and current (μV & μI). The fault detection algorithm was tested using four different supervised learning algorithms of DA, RF, KNN, and SVM through MATLAB Simulink to acquire the best detection accuracy. Then, the testing procedure of this fault detection algorithm was repeated and evaluated on medium and big-scale PV array models built in this study to validate its practicality as a multi-scale PV array fault detection algorithm.

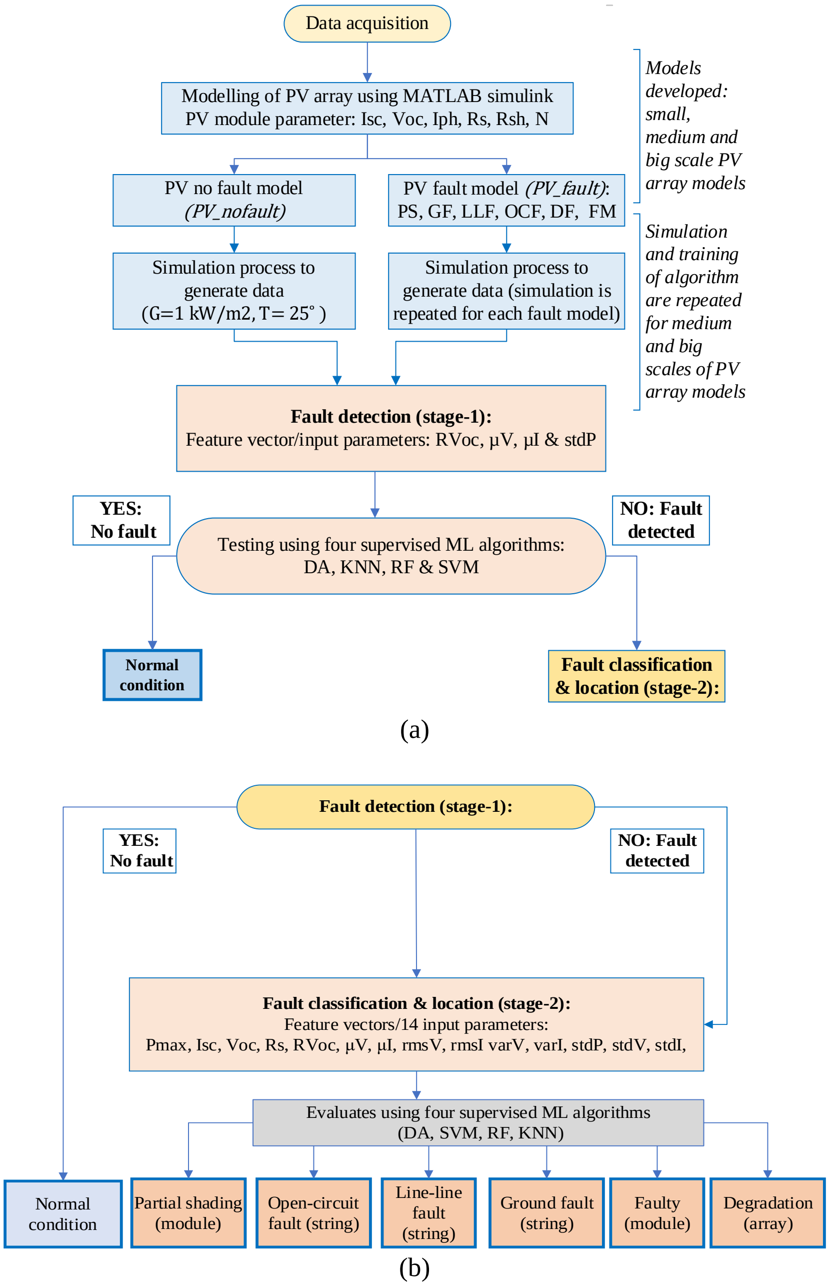


Figure 9. The flowchart of the (a) MsDs fault detection algorithm (stage-1) and (b) the MsDs fault classification and location algorithm (stage-2)

The flow chart for the stage-2 describes the testing algorithm procedure for the classification and location of faults. The stage-2 procedure can proceed if any faults are detected at stage-1. In this study, the algorithm of classification and location was tested and evaluated with the following processes:

i) The testing algorithm involved 15 data sets for $PV\_nofault$ model and 15 data sets for each GF, LLF, GA, OCF, DF, and PS PV_fault^n models.
ii) Fourteen feature vectors/input parameters of Pmax, Isc, Voc, Rs, RVoc, µV, µI, root mean square voltage and current (rmsV, rmsI), variance voltage and current (varV, varI), and standard deviations of power, voltage and current (stdP, stdV, stdI) were selected for the testing algorithm because they have been proven to produce good accuracy for PV system/array fault detection and classification [21], [26], [27].
iii) The testing algorithm used four ML algorithms, DA, RF, KNN, and SVM, to obtain the best algorithm and produce the best classification accuracy.

iv) The K-fold cross-validation method was adopted in the testing algorithm to optimize the parameter chosen and improve the classification accuracy.
v) The testing algorithm procedure at stage-2 was repeated and evaluated on medium-scale and large-scale PV array models to establish its feasibility as a multi-scale PV array fault classification and monitoring algorithm.

4. RESULT AND DISCUSSION

4.1. Simulation results and analysis of fault detection algorithm

Figure 10 shows the I-V curves generated from the simulation process using MATLAB Simulink for the small-scale PV array models that illustrates the relationship between the output voltage and the output current yielded. From the figure, it can be observed that the I-V curves generated from the simulation of $PV\_nofault$ model, and six PV_fault^n models, having different characteristics as:
i) The ISC and the VOC remain unchanged for PS simulation while the Pmax decreases.
ii) For OCF simulations, the I_{SC} and Pmax value decreases while the V_{OC} remains unchanged.
iii) For the FM simulation, the I_{SC} remains unchanged, while the V_{OC} and the gradient of the end part of the I-V curve also decrease.
iv) For the DF array simulation, the V_{OC} value remains unchanged. But the I_{SC} experienced a slight decrease, and the overall slope of the I-V curve decreased.
v) For GF simulations, the V_{OC} value increases, while other characteristics of I-V curves remain unchanged.
vi) For LLF simulations, the V_{OC} decreases while the I_{SC} remains unchanged, there is no significant change in the remaining characteristics of I-V curves.

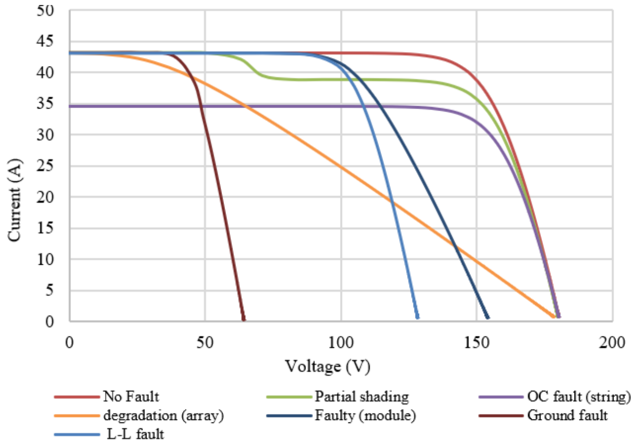


Figure 10. I-V curves of the fault and no-fault models small-scale PV arrays

Table 4 shows the testing results for the fault detection algorithm accuracies of the proposed small-scale, medium-scale, and big-scale PV array models. It can be seen that the fault detection method based on the RF algorithm has successfully acquired 100% accuracy for all PV array models. Other algorithms also achieved good accuracies, with more than 96%.

Table 4. Fault detection accuracies (small, medium & big scales PV model) using four ML algorithms

Algorithm type	Fault detection accuracy (%)		
	Small-scale PV model	Medium-scale PV model	Big-scale PV model
Discrimination Analysis	99	99	98
Random Forest	100	100	100
K-nearest neighbours	96	99	98
Support Vector Machine	97	99	100

4.2. Simulation results and analysis of fault classification algorithm

Table 5 presents the classification accuracy for small-scale, medium-scale, and large-scale PV array models developed in this study. It can be seen that the classification accuracy based on the RF algorithm is the highest compared to other algorithms, with an accuracy of more than 90% for medium and large scales PV models and almost 80% for small-scale PV models. Meanwhile, the accuracy of the testing RF algorithm for fault classification and location (module/string/array) for the six faults; DF, FM, GF, LLF, OCF, and PS of the small-scale, medium-scale, and big-scale PV array models, can be seen in Table 6.

Table 5. Fault classification accuracies (small, medium & big scales PV model) using four ML algorithms

Algorithm type	Fault classification accuracy (%)		
	Small-scale PV model	Medium-scale PV model	Big-scale PV model
Discrimination Analysis	82	90	86
Random Forest	78	90	93.3
K-nearest neighbours	48	53	55
Support Vector Machine	70	89	71

Table 6. Fault classification accuracies of six faults for small, medium, and big-scale PV model using RF algorithm

Fault	Fault classification and location accuracy (%)		
	Small-scale PV model	Medium-scale PV model	Big-scale PV model
DF (array)	93.3	93.3	86.7
FM (module)	93.3	93.3	80.0
GF (string)	50.4	100	100
LLF (string)	53.3	100	93.3
OCF (string)	86.7	80.0	93.3
PS (array)	93.3	80.0	100

It can be seen that the fault classification method based on the RF algorithm has succeeded in achieving high accuracy. Almost all fault types for all PV model scales achieve more than 90% classification accuracy, and for DF and FM (large-scale), OCF and PS (medium-scale), and OCF for small-scale get more than 80% classification accuracy. Only the fault classification for GF and LLF (small scale) achieved low accuracy.

4.3. Discussion

This study has developed and simulated MsDs algorithms for PV array fault detection, classification, and location via MATLAB/Simulink, which consists of stage-1 (fault detection algorithm), and stage-2 (fault classification and location algorithm). Although the I–V curves generated from the simulation process of the PV no-fault ($PV\_nofault$) model, and the six PV fault (PV_fault^n) models have shared the same characteristics of Voc, Isc, and Pmax (Figure 10). High accuracies were accomplished when the developed fault detection algorithm was tested using four different supervised learning algorithms; DA, RF, KNN, and SVM. The RF algorithm has achieved 100% accuracy for all scales of PV array models, as can be seen in Table 4.

For fault classification at stage-2, the RF algorithm has again achieved high accuracy for medium-scale and large-scale PV array models (more than 90%) compared to other algorithms, as shown in Table 5. Only for small-scale PV array has produced modest accuracy. However, if we look at the accuracies of fault classification and location for each PV_fault^n model as presented in Table 6, the RF algorithm with the combination of k-fold cross validation has delivered high accuracy for almost all PV array fault models (more than 90%), except for GF and LLF on the small-scale PV array achieved the low accuracy values. This might be due to the low discrimination power of ML algorithms in describing the faults, thus resulting in poor performance. In summary, the proposed MsDs has the following research contributions over earlier works [8], [28]:

i) It is low-cost and inexpensive modeling. The fault detection algorithm with the k-fold cross validation at stage-1 has proven to detect multiple common faults; GF, LLF, PS, OCF, DF, and PS in PV arrays with good accuracy and without interruption to the system.
ii) The classification and location algorithm with the k-fold cross validation at stage-2 can identify faults at different locations; at the string, module, or array level, useful for large-scale PV systems/plants, and achieved good accuracies.
iii) The study has proven that the developed algorithms are easy to execute and feasible to apply to all PV array scales globally regardless of environmental conditions.
iv) A simple fault detection algorithm at level-1 is beneficial for preventive and predictive maintenance in finding hidden faults in PV systems that CPD cannot detect. The hidden faults can reduce the system's efficiency and cause worse circumstances such as fire hazards, injuries, and electric shocks to the PV system operator.

4.4. Limitations

This study has some limitations; the MsDs technique has been tested using simulated data only. Accuracy may vary when this proposed algorithm is implemented on an actual operating PV system. Other than that, the MsDs algorithm was tested using supervised learning algorithms, in which fully labeled data were used. But for MsDs to be used for maintenance work with unlabeled data, the accuracy of the proposed algorithm is not verified. Lastly, the algorithm for fault classification and location tested on small-scale PV array models has shown moderate accuracies for GF (string) and LLF (string).

5. CONCLUSION AND FUTURE WORK DIRECTION

This study proposed a multi-scale dual-stage (MsDs) model for PV array fault detection, classification, and monitoring technique that have demonstrated good accuracy. The MsDs consists of the PV array fault detection algorithm at stage-1 and the PV array fault classification and location algorithm at stage-2. The MsDs algorithms have been tested using four supervised learning algorithms; Discriminate analysis (DA), K-nearest neighbor (KNN), Support vector machine (SVM), and Random Forest (RF), together with k-fold cross-validation in finding the best algorithm that delivers the best accuracy. Further, MsDs have also been evaluated on small, medium, and large-scale PV array models to ascertain their feasibility on multi-scale PV arrays.

The simulation results have proved that the RF algorithm has accomplished the best accuracy for both medium-scale and big-scale PV array models, with 100% accuracy for various faults (open-circuit fault, degradation array, partial shading, faulty module, ground fault, and line-line fault) detection, and more than 90% accuracy for fault classification and location, excluding for model of a ground fault and line-line fault of a small-scale PV array that produced low classification accuracy values. Overall, the simulation results have justified the study's objectives to develop a low-cost model for PV arrays with various fault detection and classification algorithms that can be implemented at various PV array scales and applicable for PV maintenance works for better efficiency, reliability, and security of the PV system.

Nevertheless, some recommendations can be carried out for future work. It is recommended to validate the proposed MsDs technique by testing developed algorithms using data from the real PV system. This ensures the accuracy of the results obtained from the developed PV array model and the actual PV system. Furthermore, the MsDs testing algorithm in this study applied supervised learning algorithms, in which fully labeled data was used. Thus, the testing algorithms need to be evaluated on unlabeled data to obtain more precise accuracy and verify the feasibility of MsDs for PV system maintenance work. Finally, more training and testing need to be done on the classification and location algorithm for the small-scale PV array models' line-line and ground faults to improve accuracy.

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REFERENCES

[1] BP, "Statistical Review of World Energy," 2020 | 69th Edition, 2020.
[2] D. S. Pillai and N. Rajasekar, "A comprehensive review on protection challenges and fault diagnosis in PV systems," *Renewable and Sustainable Energy Reviews*, vol. 91, pp. 18–40, Aug. 2018, doi: 10.1016/j.rser.2018.03.082.
[3] A. Livera, M. Theristis, G. Makrides, and G. E. Georghiou, "Recent advances in failure diagnosis techniques based on performance data analysis for grid-connected photovoltaic systems," *Renewable Energy*, vol. 133, pp. 126–143, Apr. 2019, doi: 10.1016/j.renene.2018.09.101.
[4] M. H. Ali, A. Rabhi, A. El Hajjaji, and G. M. Tina, "Real Time Fault Detection in Photovoltaic Systems," *Energy Procedia*, vol. 111, pp. 914–923, Mar. 2017, doi: 10.1016/j.egypro.2017.03.254.
[5] S. Fadhel *et al.*, "PV shading fault detection and classification based on I-V curve using principal component analysis: Application to isolated PV system," *Solar Energy*, vol. 179, pp. 1–10, Feb. 2019, doi: 10.1016/j.solener.2018.12.048.
[6] A. Hazra, S. Das, and M. Basu, "An efficient fault diagnosis method for PV systems following string current," *Journal of Cleaner Production*, vol. 154, pp. 220–232, Jun. 2017, doi: 10.1016/j.jclepro.2017.03.214.
[7] M. Dhimish, V. Holmes, B. Mehrdadi, and M. Dales, "Diagnostic method for photovoltaic systems based on six layer detection algorithm," *Electric Power Systems Research*, vol. 151, pp. 26–39, Oct. 2017, doi: 10.1016/j.epsr.2017.05.024.
[8] Z. Chen, L. Wu, S. Cheng, P. Lin, Y. Wu, and W. Lin, "Intelligent fault diagnosis of photovoltaic arrays based on optimized kernel extreme learning machine and I-V characteristics," *Applied Energy*, vol. 204, pp. 912–931, Oct. 2017, doi: 10.1016/j.apenergy.2017.05.034.
[9] Z. Yi and A. H. Etemadi, "Line-to-Line Fault Detection for Photovoltaic Arrays Based on Multiresolution Signal Decomposition and Two-Stage Support Vector Machine," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 11, pp. 8546–8556, Nov. 2017, doi: 10.1109/TIE.2017.2703681.
[10] Z. Chen *et al.*, "Random forest based intelligent fault diagnosis for PV arrays using array voltage and string currents," *Energy Conversion and Management*, vol. 178, pp. 250–264, Dec. 2018, doi: 10.1016/j.enconman.2018.10.040.

[11] S. R. Madeti and S. N. Singh, "Modeling of PV system based on experimental data for fault detection using kNN method," *Solar Energy*, vol. 173, pp. 139–151, Oct. 2018, doi: 10.1016/j.solener.2018.07.038.
[12] Y. Zhao, R. Ball, J. Mosesian, J.-F. de Palma, and B. Lehman, "Graph-Based Semi-supervised Learning for Fault Detection and Classification in Solar Photovoltaic Arrays," *IEEE Transactions on Power Electronics*, vol. 30, no. 5, pp. 2848–2858, May 2015, doi: 10.1109/TPEL.2014.2364203.
[13] M. Dhimish, V. Holmes, B. Mehrdadi, and M. Dales, "Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection," *Renewable Energy*, vol. 117, pp. 257–274, Mar. 2018, doi: 10.1016/j.renene.2017.10.066.
[14] X. Lu *et al.*, "Fault diagnosis for photovoltaic array based on convolutional neural network and electrical time series graph," *Energy Conversion and Management*, vol. 196, pp. 950–965, Sep. 2019, doi: 10.1016/j.enconman.2019.06.062.
[15] A. Haque, K. V. S. Bharath, M. A. Khan, I. Khan, and Z. A. Jaffery, "Fault diagnosis of Photovoltaic Modules," *Energy Science & Engineering*, vol. 7, no. 3, pp. 622–644, Jun. 2019, doi: 10.1002/ese3.255.
[16] E. Garoudja, F. Harrou, Y. Sun, K. Kara, A. Chouder, and S. Silvestre, "Statistical fault detection in photovoltaic systems," *Solar Energy*, vol. 150, pp. 485–499, Jul. 2017, doi: 10.1016/j.solener.2017.04.043.
[17] Z. L. X. Qing, X. Rong, J. Shengchang, Z. Lingyu, L. Yuan, "DC arc detection method based on electromagnetic radiation characteristics," *High Voltage Technology*, vol. 43, no. 9, pp. 2967–2975, 2017, doi: 10.13336/j.1003-6520.hve.20170831026.
[18] C. He, L. Mu, and Y. Wang, "The Detection of Parallel Arc Fault in Photovoltaic Systems Based on a Mixed Criterion," *IEEE Journal of Photovoltaics*, vol. 7, no. 6, pp. 1717–1724, Nov. 2017, doi: 10.1109/JPHOTOV.2017.2742143.
[19] B. P. Kumar, G. S. Ilango, M. J. B. Reddy, and N. Chilakapati, "Online Fault Detection and Diagnosis in Photovoltaic Systems Using Wavelet Packets," *IEEE Journal of Photovoltaics*, vol. 8, no. 1, pp. 257–265, Jan. 2018, doi: 10.1109/JPHOTOV.2017.2770159.
[20] N. K. Tumkur Jayakumar, M. U. Saleh, E. Benoit, J. Lacombe, M. Scarpulla, and C. Furse, "Fault Detection In PV Strings Using SSTDR," in *2018 USNC-URSI Radio Science Meeting (Joint with AP-S Symposium)*, Jul. 2018, pp. 9–10, doi: 10.1109/USNC-URSI.2018.8602847.
[21] S. R. Madeti and S. N. Singh, "A comprehensive study on different types of faults and detection techniques for solar photovoltaic system," *Solar Energy*, vol. 158, pp. 161–185, Dec. 2017, doi: 10.1016/j.solener.2017.08.069.
[22] V. Carletti, A. Greco, A. Saggese, and M. Vento, "An intelligent flying system for automatic detection of faults in photovoltaic plants," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 5, pp. 2027–2040, May 2020, doi: 10.1007/s12652-019-01212-6.
[23] S. N. A. M. Ghazali, M. Z. Sujod, and M. S. Jadin, "Forensic of Solar PV: A Review of Potential Faults and Maintenance Strategies," in *2021 International Conference on Engineering and Emerging Technologies (ICEET)*, Oct. 2021, pp. 1–6, doi: 10.1109/ICEET53442.2021.9659624.
[24] V. J. Chin, Z. Salam, and K. Ishaque, "Cell modelling and model parameters estimation techniques for photovoltaic simulator application: A review," *Applied Energy*, vol. 154, pp. 500–519, Sep. 2015, doi: 10.1016/j.apenergy.2015.05.035.
[25] B. Goss, I. R. Cole, E. Koubli, D. Palmer, T. R. Betts, and R. Gottschalg, "Modelling and prediction of PV module energy yield," in *The Performance of Photovoltaic (PV) Systems*, Elsevier, 2017, pp. 103–132.
[26] J. Zhang *et al.*, "A reinforcement learning based approach for on-line adaptive parameter extraction of photovoltaic array models," *Energy Conversion and Management*, vol. 214, p. 112875, Jun. 2020, doi: 10.1016/j.enconman.2020.112875.
[27] P. K. Ray, A. Mohanty, B. K. Panigrahi, and P. K. Rout, "Modified wavelet transform based fault analysis in a solar photovoltaic system," *Optik*, vol. 168, pp. 754–763, Sep. 2018, doi: 10.1016/j.ijleo.2018.03.131.
[28] Y. E. Yağan, K. Vardar, and M. A. Ebeoğlu, "Modeling and Simulation of PV Systems," *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, vol. 13, no. 2, pp. 1–11, 2018, doi: 10.9790/1676-1302030111.

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