A fault identification and classification algorithm for photovoltaic systems

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Abstract

With the wide application of photovoltaic (PV) systems, their work performance and maintenance are increasingly concerned. The work performance of the PV systems is affected by faults in the PV arrays and faults caused by external environmental circumstances. The current method of scheduled maintenance proves to be ineffective in fault classification. To distinguish the multiple types of faults, condition-based maintenance has been introduced, which involves the adoption of fault detection algorithms. An easy and fast fault classification algorithm based on real-time current and voltage inputs is presented in this paper to classify common faults in PV systems such as grounding fault and line-line fault. In order to develop the algorithm, an artificial neural network (ANN) is employed. Inputs and targets are obtained by simulating solar modules and outdoor conditions in Simulink. The validity of the algorithm is verified using MatLab tools.

The same type of algorithm can be applied to a broader context. By training ANN using different input and target values in different PV systems, the algorithm generated will be able to classify types of faults in these systems as well.

Key words: PV systems, condition-based maintenance, artificial neural network

Introduction

(a) Background

With the widespread use[1] of photovoltaic (PV) systems[2], their work performance and maintenance (measured by output power) are increasingly of concern to power stations and building management companies. Work performance of the PV systems is affected by the faults in the PV arrays and environmental factors.

1) Faults in PV arrays[3]
    a) Ground (GL) fault.
    b) Line-line (LL) fault.
2) External environmental circumstances include partial shading, temperature and irradiance.

(b) Motivation and aim

Currently, scheduled checkups and maintenance are adopted by most companies to ensure the expected work performance of PV systems, which is indicated by its power output. However, such maintenance is ineffective because the causes for the abnormal work performance (lower or zero power output) are often unclear[4]. Recently, condition-based maintenance[1] is introduced to better distinguish the causes of different faults, and therefore more able to accurately repair defects found in PV systems. This involves the adoption of a fault detection method. Therefore, we aim to create a fault classification algorithm in MatLab.

Methodology

Simulink[5] is used throughout our research. Firstly, temperature and irradiance on one PV module working in healthy condition (i.e. without any fault) are varied to observe how the power generated from the PV module is affected by external environmental conditions. The results can be seen in 'appendix [6].' Secondly, a simulation of a PV array under constant environmental conditions is run and various GL and LL faults are made to occur on different parts of the PV

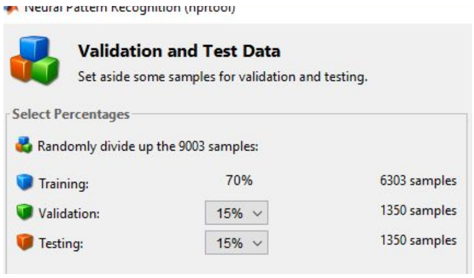
[1] Condition-based maintenance (CBM) is a maintenance strategy that monitors the actual condition of an asset to decide what maintenance needs to be done. CBM dictates that maintenance should only be performed when certain indicators show signs of decreasing performance or upcoming failure.

array. V-t and I-t graphs are plotted and patterns that are specific to a particular fault are recognised. However, this method of fault identification has limitations as explained[7] in ‘appendix.’

Thirdly, in view of the limitations of the abovementioned method, an algorithm using Neural Network Pattern Recognition tools (nprtool) is created to identify and classify faults in a PV array.[8] Different faults are simulated in the PV array and V, I values are obtained as well. Both inputs (V and I values) and targets (representations of particular types of fault) are stored in an excel sheet as our database[9].

Results analysis

Artificial neural network (ANN)[10] performs a mapping from an input space to an output space. Our fault classification algorithm utilises current and voltage values as inputs and binary representations[9] as targets which have been manually assigned to each specific case of fault.



Neural Pattern Recognition (nprtool)

Validation and Test Data

Set aside some samples for validation and testing.

Select Percentages

Randomly divide up the 9003 samples:

Training:	70%	6303 samples
Validation:	15%	1350 samples
Testing:	15%	1350 samples

Figure 1. Training, testing and validation samples

With reference to Figure 1, all samples are divided into three sets: 70% of them are used for training (learning), 15% for testing and 15% for validation. As testing samples are separated from the training samples, testing assesses learning outcome of the neural network during and after training independently. Validation is used to measure network generalisation, and to halt training when generalisation reaches the optimal level. This is achieved by monitoring the error on the validation set during the training process. (Harsha Bommana, 2019) The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set begins to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. (N.A., 2017)

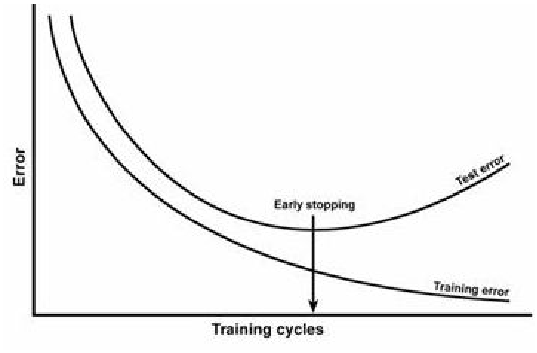


Figure 2. Test data and early stopping

With reference to Figure 2, the training process is halted at the iteration where there is minimum test error.

One of the most important steps in creating a good algorithm is selecting the number of hidden neurons. More neurons in the hidden layer (i.e. hidden neurons) means more precise calculation of internal parameter values, which allows the neural network to perform better in predicting faults. However, more precise calculation requires more time and memory of the computer to process the inputs. The below mathematical formula gives the approximate value of the number of hidden neurons:

$$N_{hidden\ layer} = \left[\left(\frac{N_{input} + N_{output}}{2}\right) + \sqrt{N_{training\ samples}}\right] \pm 10\% \quad ,$$

where $N_{hidden\ layer}$ refers to the number of neurons in the hidden layer, N_{input} refers to the number of inputs, N_{output} refers to the number of outputs, and $N_{training\ samples}$ refers to the number of training samples.

In our algorithm, there are two inputs, which are current and voltage, three outputs, which are healthy, GL and LL fault conditions, and 9003 training samples. Substituting N_{input}, N_{output} and $N_{training\ samples}$ into the equation, we get:

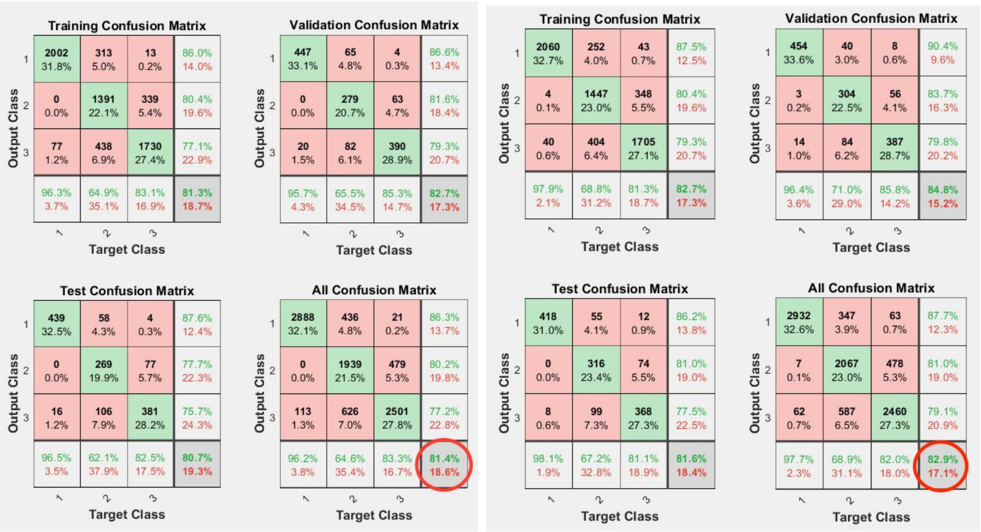
$$N_{hidden\ layer} = \left[\left(\frac{2+3}{2}\right) + \sqrt{9003}\right] \pm 10\%$$
$$= (\ 97.3841)\ \pm\ 10\%\ \ (\ 6sf\ )$$

Therefore,

$$Approximate\ \ value = 107.122\ (\ 6sf\ )\ ,$$

which means the number of hidden neurons can range from 1 to 108.

When there is only one hidden neuron, up to 51.8% of the conditions are correctly predicted after training, which means the accuracy of the algorithm is 51.8%. When there are two hidden neurons, accuracy rises to 53.0%. Three hidden neurons gives an accuracy higher than 70.0%. When the number of hidden neurons is further increased to four, a much higher accuracy of 81.4% is achieved.



Training Confusion Matrix

	1	2	3	
1	2002 31.8%	313 5.0%	13 0.2%	86.0% 14.0%
2	0 0.0%	1391 22.1%	339 5.4%	80.4% 19.6%
3	77 1.2%	438 6.9%	1730 27.4%	77.1% 22.9%
	96.3% 3.7%	64.9% 35.1%	83.1% 16.9%	81.3% 18.7%

Validation Confusion Matrix

	1	2	3	
1	447 33.1%	65 4.8%	4 0.3%	86.6% 13.4%
2	0 0.0%	279 20.7%	63 4.7%	81.6% 18.4%
3	20 1.5%	82 6.1%	390 28.9%	79.3% 20.7%
	95.7% 4.3%	65.5% 34.5%	85.3% 14.7%	82.7% 17.3%

Test Confusion Matrix

	1	2	3	
1	439 32.5%	58 4.3%	4 0.3%	87.6% 12.4%
2	0 0.0%	269 19.9%	77 5.7%	77.7% 22.3%
3	16 1.2%	106 7.9%	381 28.2%	75.7% 24.3%
	96.5% 3.5%	62.1% 37.9%	82.5% 17.5%	80.7% 19.3%

All Confusion Matrix

	1	2	3	
1	2888 32.1%	436 4.8%	21 0.2%	86.3% 13.7%
2	0 0.0%	1939 21.5%	479 5.3%	80.2% 19.8%
3	113 1.3%	626 7.0%	2501 27.8%	77.2% 22.8%
	96.2% 3.8%	64.6% 35.4%	83.3% 16.7%	81.4% 18.6%

Training Confusion Matrix

	1	2	3	
1	2060 32.7%	252 4.0%	43 0.7%	87.5% 12.5%
2	4 0.1%	1447 23.0%	348 5.5%	80.4% 19.6%
3	40 0.6%	404 6.4%	1705 27.1%	79.3% 20.7%
	97.9% 2.1%	68.8% 31.2%	81.3% 18.7%	82.7% 17.3%

Validation Confusion Matrix

	1	2	3	
1	454 33.6%	40 3.0%	8 0.6%	90.4% 9.6%
2	3 0.2%	304 22.5%	56 4.1%	83.7% 16.3%
3	14 1.0%	84 6.2%	387 28.7%	79.8% 20.2%
	96.4% 3.6%	71.0% 29.0%	85.8% 14.2%	84.8% 15.2%

Test Confusion Matrix

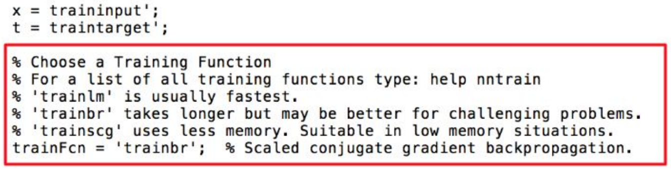
	1	2	3	
1	418 31.0%	55 4.1%	12 0.9%	86.2% 13.8%
2	0 0.0%	316 23.4%	74 5.5%	81.0% 19.0%
3	8 0.6%	99 7.3%	368 27.3%	77.5% 22.5%
	98.1% 1.9%	67.2% 32.8%	81.1% 18.9%	81.6% 18.4%

All Confusion Matrix

	1	2	3	
1	2932 32.6%	347 3.9%	63 0.7%	87.7% 12.3%
2	7 0.1%	2067 23.0%	478 5.3%	81.0% 19.0%
3	62 0.7%	587 6.5%	2460 27.3%	79.1% 20.9%
	97.7% 2.3%	68.9% 31.1%	82.0% 18.0%	82.9% 17.1%

Figure 3 and 4. Confusion matrices of training and testing results when four neurons (left) and five neurons (right) are selected in the hidden layer.

With reference to Figure 3 and 4, when the number of hidden neurons increases from four to five, the performance of the algorithm in terms of accuracy of fault prediction increases from 81.4% to 82.9%, which does not significantly increase the accuracy of our fault classification algorithm. As the number of hidden neurons keeps increasing, the performance of the algorithm remains almost unchanged, while the time taken to run the algorithm increases significantly. Hence, any further increase in the number of hidden neurons, and thus the resulting negligible improvement in accuracy of fault prediction, is not worth the time prolonged in running the algorithm. With this consideration in mind, only four neurons are chosen in the hidden layer.



```
x = traininput';
t = traintarget';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainbr';  % Scaled conjugate gradient backpropagation.
```

Figure 5. A section of the report showing training functions

With reference to Figure 5, upon finishing training the algorithm, a report consisting of MatLab code is saved. In the report, not only the number of hidden neurons can be changed, but also training functions. Various training functions including “trainlm”, “trainbr” and “trainscg” have their respective advantages. “Trainlm” involves the shortest training time but cannot be used in complex algorithms. “Trainbr” takes longer to run but may be better for challenging problems. “Trainscg” uses less memory than the other two training functions. In our algorithm, “trainbr” gives the best result.

Discussion

(a) Risk assessment

Our entire research will be conducted in MatLab on the computer. No hazardous chemicals, activities, or devices will be used. No safety precautions or procedures are needed either.

(b) Limitations

Firstly, this algorithm is not universally applicable for fault prediction in all other PV arrays.

The algorithm is established based on the unique characteristics of our array[2]. Thus, given a different PV array, a different database of V, I values and binary representations has to be redesigned[11].

Secondly, there is a limit to the highest possible accuracy in fault prediction. When only four hidden neurons are selected, the accuracy cannot be increased beyond 82%. Although increasing the number of hidden neurons can still minimally increase the accuracy, this fails to align with the practical concern that the time taken for running the algorithm should not be so long that the algorithm gives delayed classification results, affecting maintenance operations. Furthermore, even if the number of hidden neurons increases to its upper limit[3], the algorithm is still unable to achieve the desired accuracy of over 99%, which is much higher than the highest accuracy possible for our algorithm. Our algorithm, which only uses the raw values of V and I, is less accurate in fault prediction as compared to more advanced fault prediction methods.

(c) Future work

The algorithm fails to hit the desired accuracy, which is over 99%. Considering the trade-off among cost, time and accuracy, the current accuracy can be further improved. To achieve this, the total error should be at the minimum, which requires a balance between low *variance*[4] and low *bias*[5] of the algorithm, where the sum of the *bias*^{2} and the *variance* is at the minimum.[12] This can be achieved by the following methods. (Sunil Ray, 2015)

[2] Unique characteristics of our array refer to the number of PV modules and/or the way of connection of various electrical components in the PV array.

[3] The upper limit is 108, as calculated in “results analysis.”

[4] *Variance* refers to the algorithm's sensitivity to specific sets of training data.

[5] *Bias* is the difference between the model's expected predictions and the true values. *Bias* occurs when an algorithm has limited flexibility to learn the true signal from the dataset.

Method 1: Add more data. Presence of more data results in more accurate algorithms, since increasing the size of training data allows the algorithm to establish a more accurate functional relationship between input space and output space.

Method 2: Treat outliers. The unwanted presence of outlier values in the training data often reduces the accuracy of a model or leads to a biased model. This leads to inaccurate predictions, because the functional relationship derived from the abnormal input-target datasets will deviate from that derived from the normal input-target datasets. In such cases, outliers can be treated separately or deleted, both reducing the *variance* on the algorithm.

Method 3. Feature engineering. Feature engineering helps to extract more information from existing data. New information is extracted that have a higher ability to explain the patterns in the training data.

Method 4. Algorithm tuning. The objective of parameter tuning is to find the hyperparameters' optimal values[13]. When the hyperparameters are not at optimal values, the problem of overfitting or underfitting will occur. A powerful preventative measure to reduce overfitting is cross validation, where multiple mini train-test splits are generated from the initial training data. As a result, hyperparameters are tuned with only the original training set, which allows the test set to be isolated from the training set.

The above-mentioned methods were not done because they are not within the capability of the software that we are currently using, and because of time constraints. We will explore other programming tools in the future to shorten the time for training the algorithm, to treat outliers and to actualise feature engineering and algorithm tuning.

Conclusion

This fault identification and classification algorithm has several benefits. Firstly, it is able to monitor, track and report the current working condition of a PV array so that any fault happening in the PV array can be detected, classified and fixed in time. Secondly, as one type of condition-based maintenance, the algorithm saves time and labour cost than scheduled checkups.

The procedure of the fault identification and classification algorithm can be summarized as follows. When real-time voltage and current values are fed into the algorithm, the algorithm maps the input to the output using the functional relationship described by the internal parameters. The output generated will clearly indicate one specific case[9], and therefore one type of working condition[11].

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Appendix

[1] The widespread use of PV systems. Photovoltaic (PV) systems have gained great popularity since the 1970s for its environmental benefits. PV systems utilise solar energy to generate electricity, which is a cleaner source of energy for power generation as compared to conventional means such as combustion of fossil fuels. It is also more accessible to remote regions where conventional grid access is impractical due to the long distance over which the transmission lines have to be constructed. In Singapore, rooftop solar PV systems have already been installed at several local waterworks. By 2021, enough solar energy will be provided to power the equivalent of 15,500 four-room HDB flats for one year. (N.A., 2019)

[2] A brief introduction to PV arrays

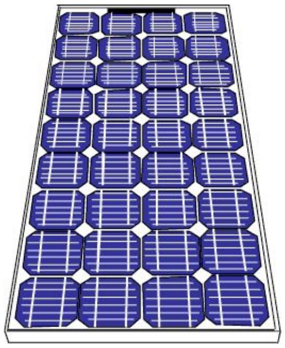


Figure 6. A typical bulk silicon PV array used in outdoor remote power applications.

With reference to Figure 6, a PV module consists of a number of interconnected solar cells[6] encapsulated into a single, long-lasting, stable unit. A PV array is a linked collection of PV modules.

[3] Faults in PV arrays

a) Ground (GL) fault. GL fault occurs when one of the cables connecting the PV modules touches the ground. It is usually caused by insulation breakdown.

[6] A solar cell, or photovoltaic cell, is an electrical device that converts the energy of light directly into electricity by the photovoltaic effect, which is a physical and chemical phenomenon.

b) Line-line (LL) fault. LL fault occurs when two cables connecting the PV modules accidentally touch each other. This happens because the two PV modules in a PV array are in close proximity.

[4] The challenge faced by maintenance of PV systems: unclear causes for the abnormal work performance (lower or zero power output). The information available from the PV systems is limited to current and voltage only, which is insufficient to attribute the abnormal work performance to any specific cause. The challenge in distinguishing the causes of abnormal work performance (faults in the PV arrays and environmental factors) results in substantial labour and financial resources employed to ascertain the exact cause and the exact location where the cause occurs on a huge solar panel.

[5] The function of Simulink. Simulink simulates the actual working conditions of PV systems, where external environmental conditions vary and faults in PV arrays can be present or absent. Voltage (V), current (I) and power (P) values can be obtained each time we run the Simulink.

[6] Relationships between external environmental conditions and maximum achievable power from a PV module. After running the simulation multiple times with different temperature and irradiance values, graphs showing relationships between external environmental conditions and maximum achievable power from a PV module are obtained.

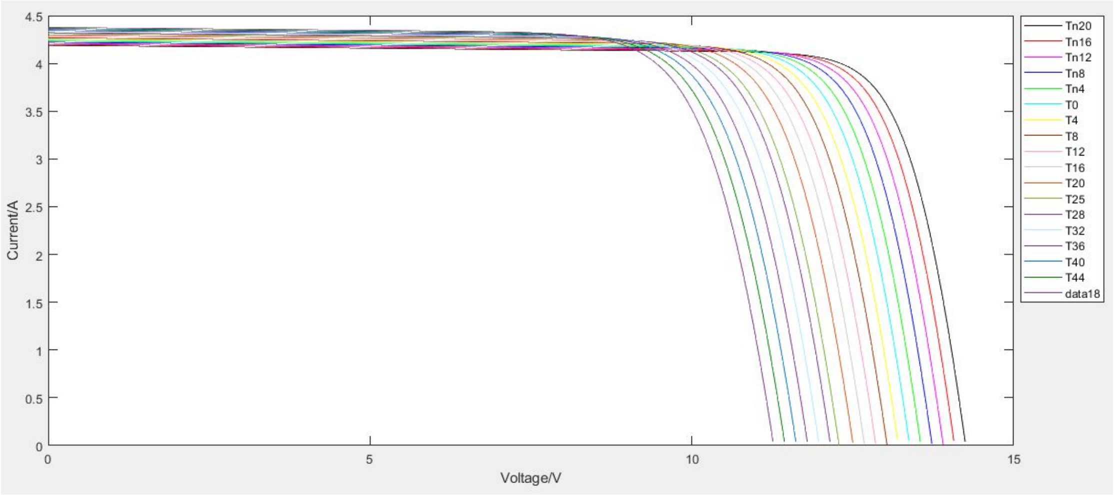


Figure 7. I-V graph of one PV module receiving constant irradiance[7] (500 Wm^{-2}) at varying temperatures

With reference to Figure 7, when the temperature increases, short-circuit current[8] (I_{SC}, indicated in the graph as intercepts on x-axis) increases and open-circuit voltage[9] (V_{OC}, indicated in the graph as intercepts on y-axis) decreases. However, the increase in I_{SC} is smaller than the decrease in V_{OC} , resulting in an overall decrease in magnitude of achievable power. This is because an increase in temperature will increase the resistance inside semiconductor materials, hindering the movement of excited electrons and holes. As a result, power output is lower as temperature rises.

[7] The solar irradiance is the output of light energy from the entire disk of the Sun, measured at the Earth. (NASA)

[8] The short-circuit current is the current through the solar cell when the voltage across the solar cell is zero (i.e., when the solar cell is short circuited) (pveducation.org)

[9] The open-circuit voltage, VOC, is the maximum voltage available from a solar cell, and this occurs at zero current. (pveducation.org)

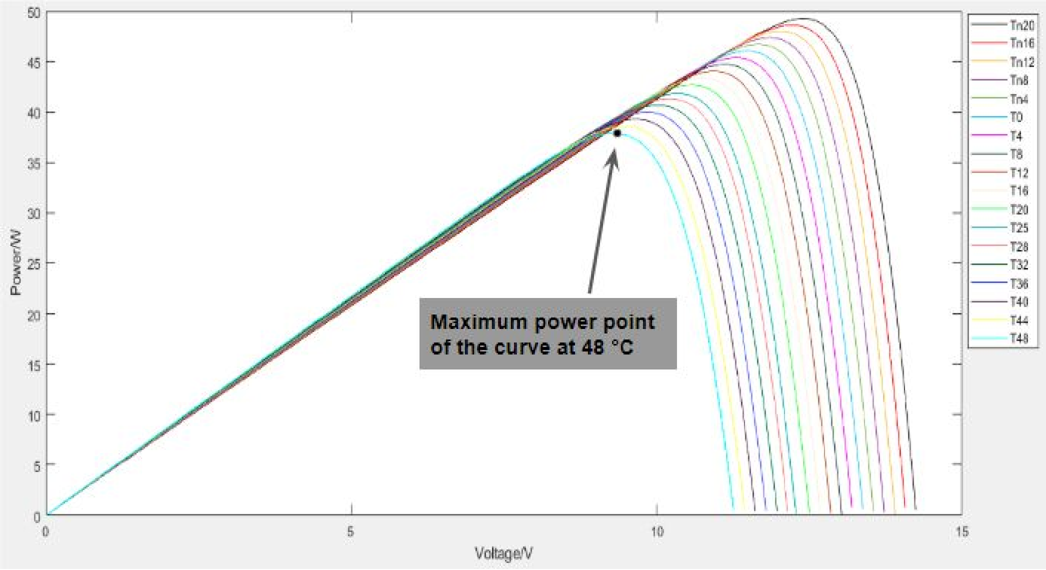


Figure 8. P-V graph of one PV module receiving constant irradiance (500 Wm^{-2}) at varying temperatures

With reference to Figure 8, the maximum power point (MPP)[10] decreases with increasing temperature. This tallies with our analysis above.

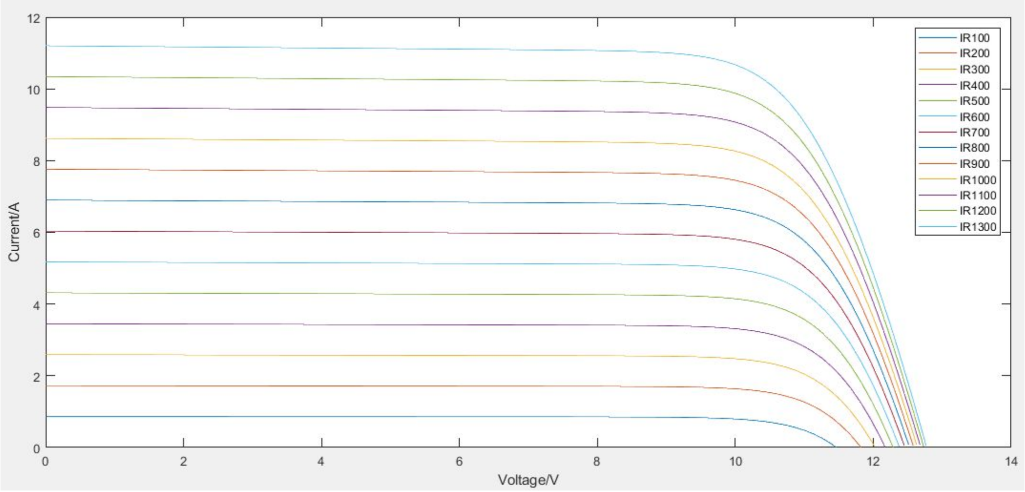


Figure 9. I-V graph of one PV module at constant temperature (25 °C) receiving varying irradiance

[10] Maximum power point (MPP): The point on a power curve that has the highest value of the product of its corresponding voltage and current, or the highest power output. (pveducation.org)

With reference to Figure 9, both I_{SC} and V_{OC} increase when solar irradiance increases, causing the MPP to increase. This is because when a PV module receives higher solar irradiance, it absorbs more photons and excites electrons at a faster rate in the semiconductor material at the P-N junction. As a result, power output increases.

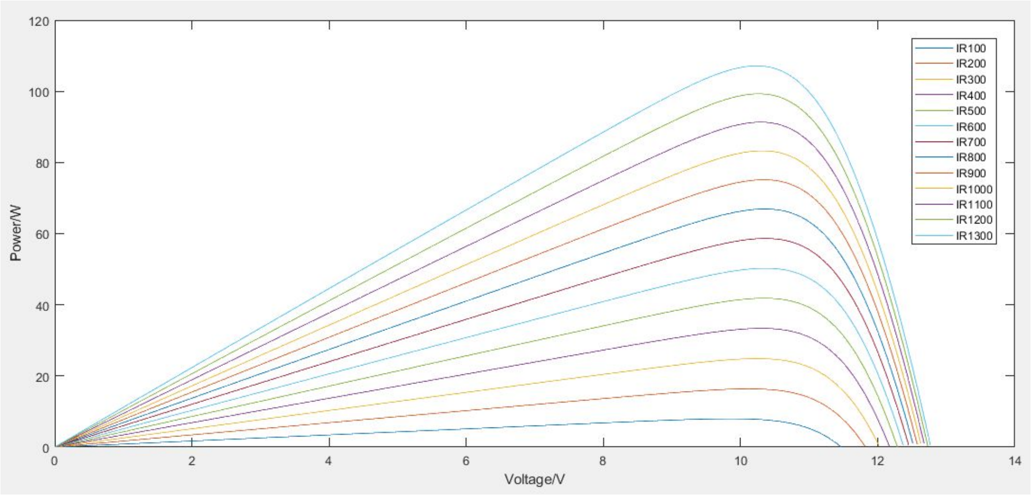


Figure 10. P-V graph of one PV module at constant temperature (25 °C) receiving varying irradiances

With reference to Figure 10, the MPP increases with increasing irradiance. This also tallies with our analysis above.

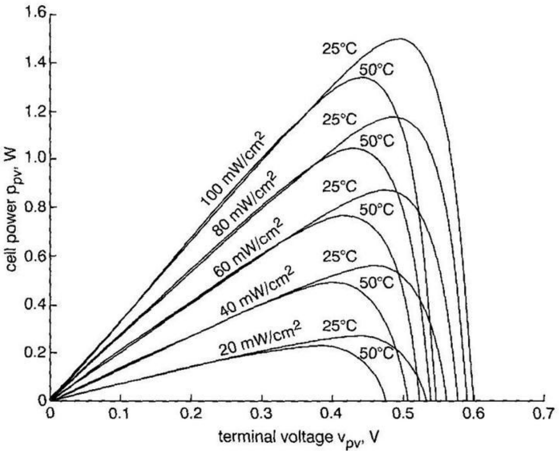


Figure 11. Combined effect of temperature and irradiance on MPP (Safak Saglam, 2019)

In conclusion, the MPP of a PV module increases with increasing irradiance and decreasing temperature, as shown in Figure 11.

[7] Graphs of patterns that may be specific to a particular fault. A simulation of a PV array consisting of six PV modules is used. With constant temperature and irradiance, the simulation is run for four seconds and various GL and LL faults are made to occur on different parts of the PV array at the third second. Graphs of output voltage and current are plotted. On the graph, patterns that are specific to a particular fault are recognised. The fault is only made to occur at the third second because drastic changes in V and I values depicted in the graph before and after the fault happens can help us identify the particular fault type.

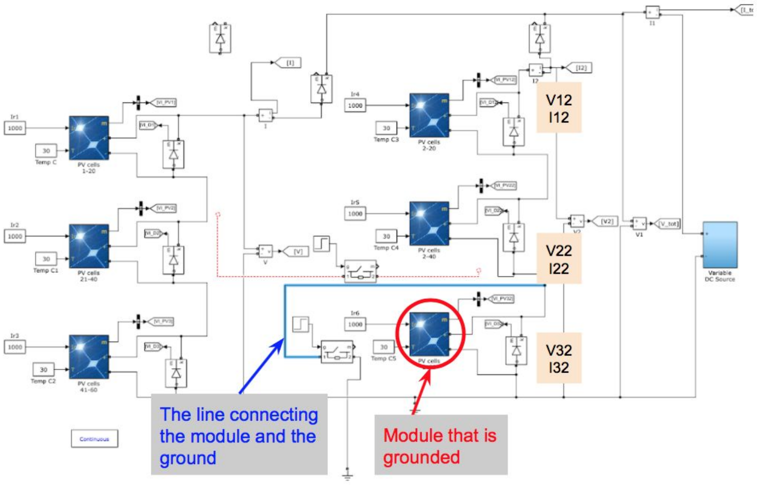


Figure 12. When GL fault occurs in a PV array

Figure 12 illustrates a typical PV array consisting of six PV modules, one of which is connected to the ground. The temperature and irradiance are fixed at 30°C and 1000Wm^{-2} respectively. Since GL fault is made to occur in the series on the right, it is only necessary to analyse the V-t and I-t graphs of the three PV modules in the series on the right for fault identification purpose.

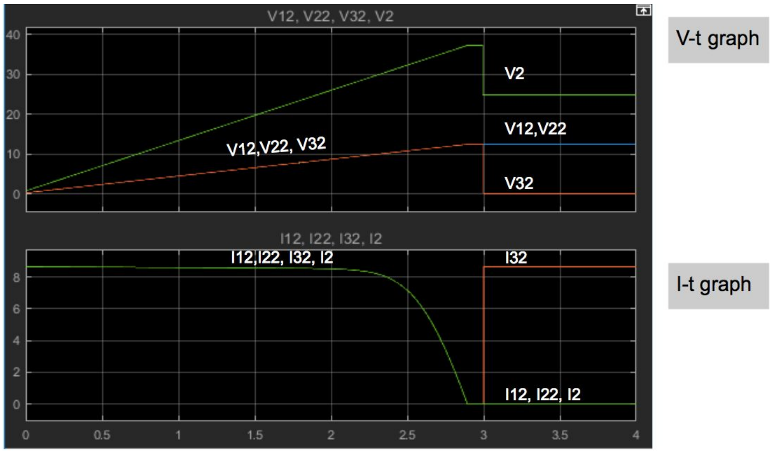


Figure 13. V-t and I-t graphs of the three PV modules in the series on the right

With reference to Figure 13, the simulation is run for four seconds. At the third second, GL fault is made to occur on the PV module circled. The upper graph shows four lines, representing the voltage output (V12, V22, V32) of each PV module and the resultant output (V2). In particular, V32 represents the voltage output of the grounded module. At the third second, the voltage generated across the faulty module is reduced to zero because once the module is connected to the ground: The potential difference across the circled module will be equal to the potential of the ground which is zero. And the other two modules continue to generate the same voltage output as before. In the lower graph, current output of each PV module and the resultant current (I2) are shown. At the third second, the bottom right module is grounded, and the current flowing through that module is separated from the current in the series that connects the two modules above. As a result, the current through the faulty module, which is indicated as I32, is no longer equal to the value of I2, I12 and I22, but rather spikes to the maximum due to the negligible resistance of the wire through which the current flows from the faulty module to the ground.

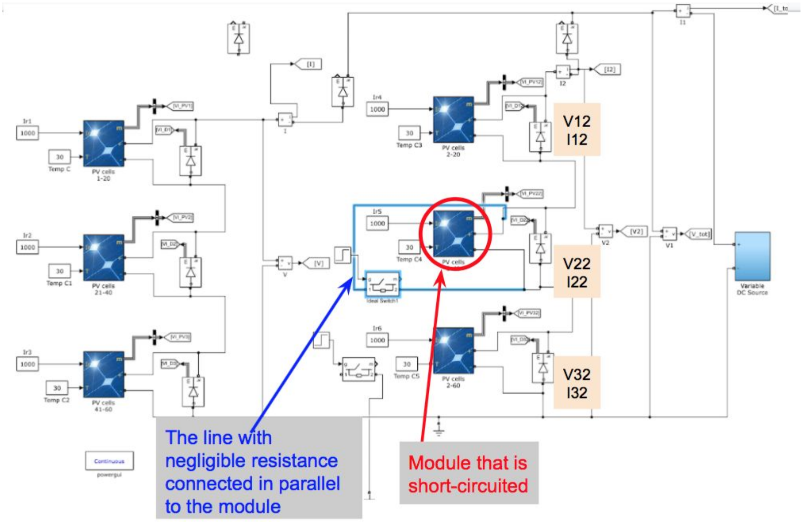

V12
I12
V22
I22
V32
I32
The line with negligible resistance connected in parallel to the module
Module that is short-circuited
Variable DC Source

Figure 14. When LL fault occurs in a PV array

Figure 14 shows a PV array consisting of six PV modules. The PV module circled is short-circuited. The temperature and irradiance are fixed at 30°C and 1000Wm^{-2} respectively. Similar V-t and I-t graphs of the PV modules in the series on the right are shown in Figure 11.

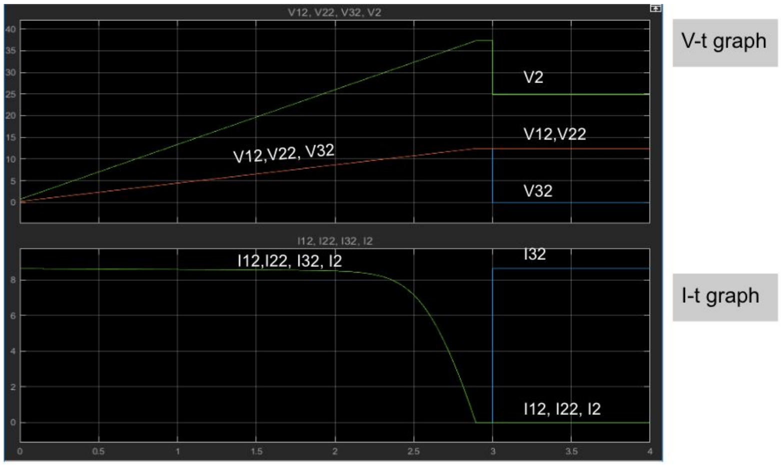


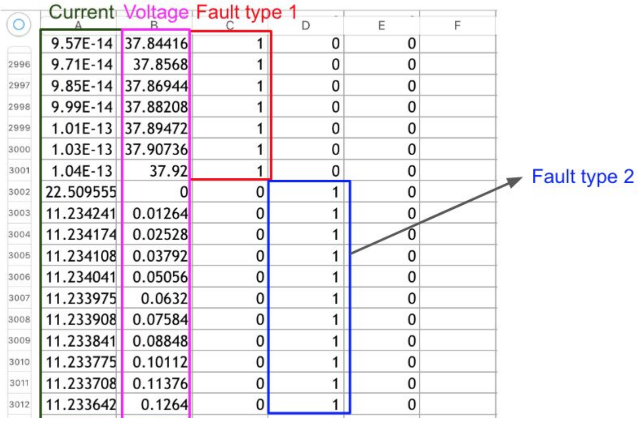
Figure 15. V-t and I-t graphs of the three PV modules in the series on the right

With reference to Figure 15, the simulation is run for four seconds and LL fault is made to happen at the third second. When LL fault happens, the measured voltage is immediately reduced to zero because the potential difference across the line with negligible resistance is zero. As the circled module is short-circuited, the current in the series flows through the line, which is an ohmic conductor, rather than the circled PV module, which is a PV semiconductor. Therefore the current through the faulty module spikes to the maximum.

However, it is not hard to see that Figure 13 and Figure 15 give exactly the same graph though different faults are made to happen. By mere observation of V-t and I-t graphs, it is clear to see whether GL fault or LL fault occurs, but not to distinguish which fault it is exactly. In order to identify which fault has occurred, more advanced tools have to be adopted.

[8] In this method, unlike the second simulation, the simulation is run for three seconds only, with the fault being made to occur at the start. The timing at which the fault is made to occur in this method is different from that outlined in the previous method, because the input data fed into the algorithm should only comprise of the V and I values under faulty conditions, instead of those under both healthy and faulty conditions.

[9] Illustration of the database



	Current	Voltage	Fault type 1			
○	A	B	C	D	E	F
	9.57E-14	37.84416	1	0	0	
2996	9.71E-14	37.8568	1	0	0	
2997	9.85E-14	37.86944	1	0	0	
2998	9.99E-14	37.88208	1	0	0	
2999	1.01E-13	37.89472	1	0	0	
3000	1.03E-13	37.90736	1	0	0	
3001	1.04E-13	37.92	1	0	0	
3002	22.509555	0	0	1	0	
3003	11.234241	0.01264	0	1	0	
3004	11.234174	0.02528	0	1	0	
3005	11.234108	0.03792	0	1	0	
3006	11.234041	0.05056	0	1	0	
3007	11.233975	0.0632	0	1	0	
3008	11.233908	0.07584	0	1	0	
3009	11.233841	0.08848	0	1	0	
3010	11.233775	0.10112	0	1	0	
3011	11.233708	0.11376	0	1	0	
3012	11.233642	0.1264	0	1	0	

Figure 16. A section of the database where inputs (V and I values) and targets (particular types of fault) are stored

With reference to Figure 16, current values are recorded in the first column and voltage values are recorded in the second column. The third column to the fifth column contain binary representations[11] that are targets of each set of current and voltage values. Each column recording the targets represents a particular condition (i.e. healthy condition, a specific case of GL fault and a specific case of LL fault). Character “1” present in the column means the fault corresponding to that column occurs, while character “0” present in the column means the fault corresponding to that column does not occur. As shown on Figure 16, a small database[12] containing V, I values and targets is created for presentation purpose. In a bid to train the algorithm, current and voltage values are fed into the neural network as inputs and binary representations are also keyed in as desired targets.

[10] A brief introduction to artificial neural network

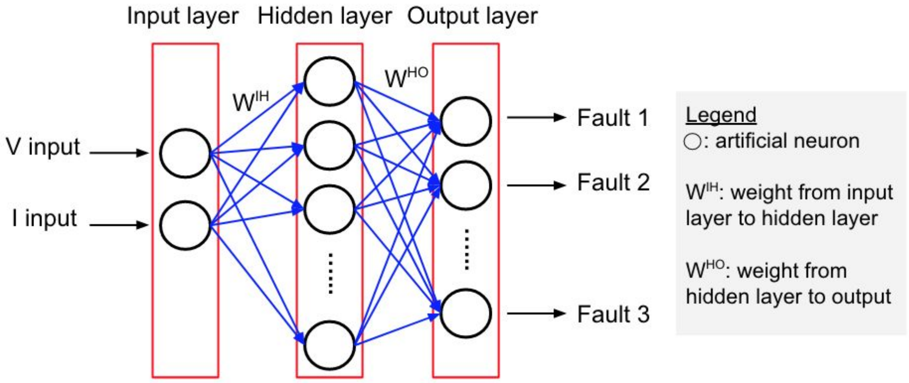


Figure 17. Illustration of how a simple artificial neural network works

An artificial neural network (ANN) is an interconnected group of nodes, inspired by a simplification of neurons in a brain (Luke Dormehl, 2019). With reference to Figure 17, each circular node represents an artificial neuron and a blue arrow represents a connection from the output [13]of one artificial neuron to the input of another. Here are some key definitions in ANN:

[11] Binary is a base-2 number system that uses two mutually exclusive states to represent information. A binary number is made up of elements called bits where each bit can be in one of the two possible states. Generally, we represent them with the numerals 1 and 0.

[12] This database only includes three specific cases, containing 9003 samples, 3001 for each case (i.e. healthy condition, a specific case of GL fault and a specific case of LL fault)

[13] Output of the algorithm is the result produced by the algorithm after training, when only input value is given, which will not always be correct.

1) Input layer. Number of neurons in this layer corresponds to the number of inputs to the neural network. Neurons in this layer only transmit signals to the following layer.
2) Hidden layer. This layer has an arbitrary number of neurons. Neurons in this layer are involved in signal modification.
3) Output layer. The number of neurons in the output layer corresponds to the number of the output values of the neural network.
4) Weight. This is represented in matrix and shows the strength of the connection between units. For example, a weight that is nearly zero means changing the input will hardly change the output. (Kailash Ahirwar, 2017)

ANN has a wide range of applications when different ANN architectures or learning methods and rules are applied. These applications include classification, pattern matching, optimisation, function approximation and data mining. Our algorithm is a classification algorithm that classifies fault types into healthy, GL fault and LL fault conditions.

ANN performs a mapping from an input space to an output space. Through analysing the instances of inputs and desired targets[14] fed into the ANN, the algorithm will work out the optimised internal parameter values that can most accurately describe the unknown functions mapping inputs to targets. This process is known as learning or training, whereby a process model is developed based only on observations of its input-output behavior. In the process, values of internal parameters are adjusted to minimize the squared error between the outputs produced by the network and the desired targets. Therefore, ANN will eventually be able to map new inputs to outputs that are most close to the targets without prior knowledge.

For simple illustration, given sample images of individual swans and geese (input) that have been manually labeled as “swan” or “goose” (target), the algorithm will analyse and learn specific characteristics exclusively associated with swans and geese respectively. Successful learning outcome will capture unknown functional relationship between the input and target. This learning process is also known as the discovery of hidden patterns. Eventually, the algorithm will be able to classify other images containing geese and swans based on the

[14] Targets are correct output values given to the algorithm, for training purposes.

established patterns without any prior knowledge. The same mechanism applies for the algorithm classifying various fault types in a PV system.

[11] The rationale for redesigning database. For instance, our PV array has six PV modules and a total of fifteen different cases[15] belonging to the three working conditions. When the number of PV modules and/or the way of connection of various electrical components in the PV array change(s), the number of cases belonging to the three working conditions, as well as V and I values as inputs, will vary.

[12]

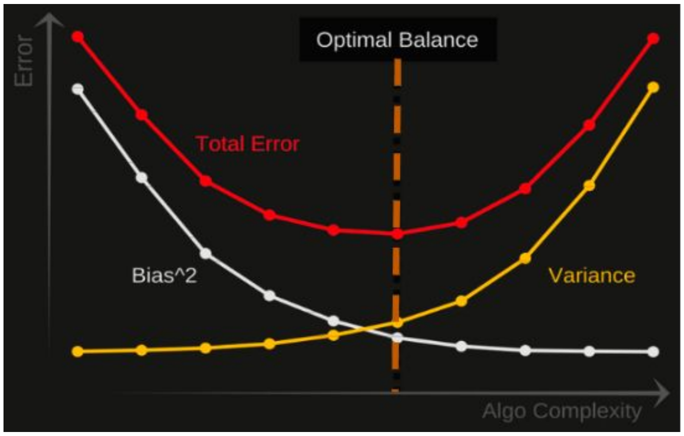


Figure 18. Optimal balance achieved at the *lowest total error.*

With reference to Figure 18, total error[16] is at the minimum point when the sum of the bias2 and the variance is the minimum. However, an algorithm with low bias tends to have high variance, and an algorithm with low variance tends to have high bias. Hence, low bias and low variance cannot be achieved simultaneously.

[15] Fifteen cases refers to specific cases of the three working conditions, three of which is mentioned under "Results analysis." Among the fifteen cases, healthy condition has one case, GL fault has three cases and LL fault has eleven cases.

[16] *Total Error = Bias^2 + Variance + Irreducible Error. Irreducible error* cannot be reduced algorithms. It can sometimes be reduced by better data cleaning.

[13] Hyperparameters[17] are parameters, for example, constraints, weights, number of hidden layers and learning rates[18], that control the learning process of the algorithm. In particular, if the learning rate is too low, the neural network will miss the important patterns in the data, resulting in underfitting; conversely, if the learning rate is too high, the algorithm will be too complex, that it memorises the noise instead of the signal, resulting in overfitting. (Jason Brownlee, 2019)

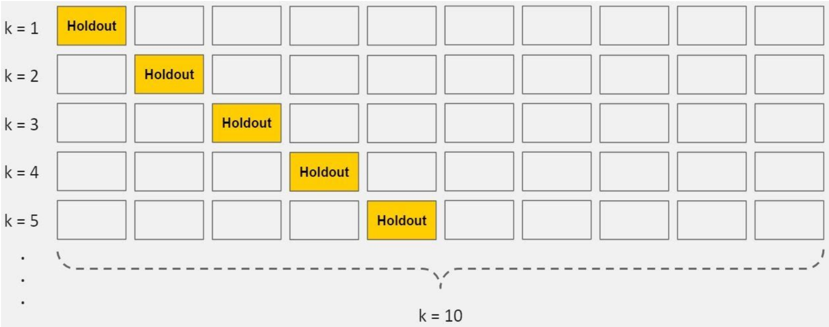


Figure 19. K-fold cross-validation

A powerful preventative measure to reduce overfitting is cross validation. With reference to Figure 19, in standard k-fold cross validation, multiple mini train-test splits are generated from the initial training data. Data is partitioned into k subsets, called folds. The algorithm is then iteratively trained on k-1 folds while the remaining folds are used as the test set (holdout fold).

[17] A hyperparameter is different from the ‘internal parameter’. A hyperparameter is a parameter whose value is used to control the learning process of the neural network. By contrast, an internal parameter (typically a node weight), which describes the functional relationship between the inputs and targets, is learned in the learning process.

[18] Learning rate refers to the step size, which is the amount that the weights are updated during each iteration of the training process. It has a small positive value, often in the range between 0.0 and 1.0.

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