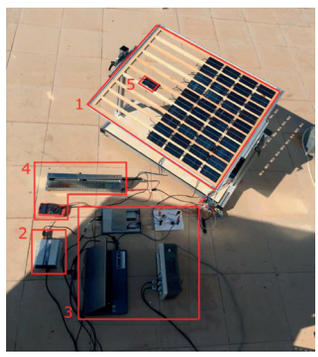
Fault detection in photovoltaic arrays: a robust regularized machine learning approach



Detección de fallos en conjuntos fotovoltaicos: un enfoque robusto y regularizado de aprendizaje de máquina

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RESUMEN

- En este artículo, se propone un método robusto basado en datos para la detección de fallos en conjuntos fotovoltaicos (PV). Nuestro método se basa en las redes de enlace funcional de vectores aleatorios (RVFLN) que tiene la ventaja de asignar aleatoriamente parámetros en capas ocultas sin necesidad de ajuste. Para eliminar el efecto del ruido de medición y el exceso de sobreentrenamiento en el proceso de formación que reducen la precisión de la detección de fallos, se utiliza el método de regularización dispersa que emplea la norma l2 con factor de ponderación de la pérdida para calcular los pesos de salida. Para lograr una gran robustez frente a las muestras atípicas, se emplea la estimación no paramétrica de la densidad del núcleo para asignar un factor de ponderación de la pérdida. Mediante una simulación rigurosa y estudios experimentales, validamos el rendimiento de nuestro método propuesto para detectar los fallos de cortocircuito y de circuito abierto basándonos únicamente en las mediciones de corriente y voltaje de salida de los conjuntos fotovoltaicos. Además de una mayor robustez en comparación con la máquina de vector de soporte menos cuadrado, también mostramos que nuestro método propuesto proporciona una precisión media de detección del 80% y el 100% para cortocircuito y circuito abierto, respectivamente.
- **Palabras clave:** Análisis de correlación canónica, detección de fallos, conjunto fotovoltaico, red de enlace vectorial aleatorio, regularización dispersa.

ABSTRACT

In this paper, a robust data-driven method for fault detection in photovoltaic (PV) arrays is proposed. Our method is based on the random vector functional link networks (RVFLN) which has the advantage of randomly assigning hidden layer parameters with no tuning. To eliminate the effect of measurement noise and overfitting in the training process which reduce the fault detection accuracy, the sparse-regularization method is utilized which uses l2-norm with loss weighting factor to compute the output weights. To attain strong robustness against the outlier samples, the non-parametric kernel density estimation is employed to assign a loss weighting factor. Through rigorous simulation and experimental studies, we validate the performance of our proposed method in detecting the short and open circuit faults based on only the output current and voltage measurements of PV arrays. In addition to stronger robustness comparing with the least square-support vector machine, we also show that our proposed method provides 80% and 100% average detection accuracy for short circuit and open circuit, respectively.

Key Words: Canonical correlation analysis, fault detection, photovoltaic array, random vector-link network, sparse regularization.

1. INTRODUCTION

Despite advanced technologies in photovoltaic (PV) power generation deployment, PV systems are exposed to the faults that negatively affect their efficiency and profitability. Undetected faults in PV systems may lead to loss of power in the system as well as fire-hazards and safety issues. Conventional protection and fault detection methods used in PV systems include overcurrent protection devices (OCPDs), ground fault detection interrupters (GFDI) and fuses [1, 2]. However as demonstrated in the literature, the faults occurring under low mismatch and high impedance conditions do not change the output of PV arrays comparing to their operation under normal conditions, thus they are not detectable by the conventional methods and without suitable fault detection algorithms [3]. Besides, the blocking diodes protecting the system from back feeding current and active maximum power point tracking (MPPT) module may mask the faults; in the case of blocking diodes, the induced back-feeding current is insufficient to melt the protective fuses; when MPPT is active, although the back feeding current exceeds the fuse threshold, it is suddenly lowered down by MPPT, meaning that it is insufficient to melt the fuse [4].

In the literature, numerous PV fault detection and diagnosis methods have been proposed which are classified under two groups: model-based and data-driven. In the model-based approaches, the real-time measurement data is compared with the parameters of the analytical PV model to detect the faults [5–9]. Regarding the model-based methods, an effective kernel generalized likelihood ratio test method is used in [5] for the detection of the faults in low mismatch and partial shading conditions, and the authors in [6] propose a method based on I-V characteristics of PV system for the detection of short-circuit (SC) and open-circuit (OC) faults; a statistical approach is proposed in [7] using a one-diode model for the detection of SC, OC and partial shading faults; in [8], DC-side faults are detected by a method comparing estimated PV array parameters and actual measurements, in which the method recognizes the faulty condition using the eagle strategy-based hybrid adaptive Nelder-Mead simplex algo-

rithm; to detect the ground, OC and bridge faults, the authors in [9] propose to use the fractional-order colour relation classifier. Although the model-based methods require less equipment and are applicable to a variety of PV systems, they have low fault detection accuracy due to the difference between the actual system and the simulated model, similar operation under low mismatch and high impedance conditions, non-linear operation characteristics of PV systems and ever-changing environmental conditions.

In the data-driven approaches, however, the collected data from the PV system operation is used to extract the faults' features and detect them in real-time using measurement data [10–15]. Various methods based on signal processing, computational intelligence and machine learning techniques have been proposed by the researchers; unsupervised-based dilation and erosion clustering algorithms are proposed in [10] for the detection of SC and OC faults; using wavelet-based artificial neural network (ANN), an algorithm is developed in [11] for the fault detection on both DC and AC sides of the PV system; in [12], SC and partial shading faults are detected by the wavelet packet transforms using only MPPT information; the authors in [13] propose the support vector machine (SVM) based on the multi-resolution signal decomposition (MSD) to detect the SC faults, while an MSD-based fuzzy reference system is proposed in [14] for SC and ground faults detection; an algorithm called graph-based semi-supervised learning is proposed in [15] for the detection of SC and OC faults. Although those methods have shown an acceptable accuracy, they might not be practical due to the requirement of large training data, time-consuming training steps, parameter setting, sensitivity to the measurement noise, possible overfitting, and low generalization performance.

To address the issues discussed above, we propose a new method based on the random vector functional-link networks (RVFLN) for SC and OC faults detection in the PV system. Our proposed method works using the output current and voltage measurements of PV array. The features used to distinguish faulty conditions from normal operation are derived from the recorded current and voltage measurements. To decrease the computational complexity of the detection method and increase the efficiency of algorithm, the dimension of the extracted features are reduced by the canonical correlation analysis (CCA). Then, a sparse-RVFLN system is built, and finally the trained sparse-RVFLN system is tested using unseen actual data for model evaluation and performance. The contributions of this work are as follows:

- To the best of our knowledge, CCA for the first time is introduced for PV fault detection which helps to increase detection accuracy in case of hard-to-detect faults, e.g. high impedance and low mismatch SC faults.
- Our method processes large scale real-time data, and it shows a faster learning procedure than the reported conventional methods in the literature.
- RVFLN weights are calculated using sparse regularization, which not only increases the fault detection accuracy, but also strengthens its robustness against the outlier samples resulting from overfitting, measurement noise, and sensor and measurement errors which are missing in most of the conventional methods.

2. PV FAULT DETECTION METHOD

In this section, we first show how feature vectors are constructed based on the output voltage and current measurements of PV array. Then, CCA, which provides the distinctive properties to algorithm for high impedance and low mismatch SC faults, is used to create a new feature space. Finally, the sparse-RVFLN classifier using l_2-norm and non-parametric kernel density estimation(NKDE) to reduce the impact of the noise are introduced.

2.1. DATA PRE-PROCESSING

2.1.1. Feature Construction

To detect the faults occurring in PV array and distinguish them from normal system operation, the feature vectors must be constructed from the measured output current and voltage. To cover different faults, we construct 10 feature vectors which are listed in Table 1.

Among the feature vectors, the first two (F1 and F2) are obtained by normalizing the measured current and voltage to ensure the applicability of the proposed algorithm to the PV systems with various size and avoid re-tuning the parameters. IMPP and VMPP are, respectively, the maximum current and voltage, and ISC_Array and VOC_Array denote the SC current and OC voltage, respectively. The third feature (F3) is the fill factor indicating the maximum normalized power to be supplied by the PV array. Although both irradiation variation and faults change the fill factor, the faults in the system result in more abrupt changes comparing to the irradiation. Thus, using the fill factor is effective in detecting the SC faults. As the shape of I-V curve is significantly affected by partial shading, the fourth feature (F4), which refers to the area under the curve, is used to distinguish the faults from partial shading occurring under normal operating conditions. The fifth feature (F5) describes the derivative of conductance, and the sixth feature (F6) aims to reduce the effect of irradiation on conductance as any variation in irradiation changes F5. The seventh feature (F7), i.e. the rate of change of conductance at VOC, and the eighth feature (F8) is mVOC, which refers to the rate of change of conductance at the middle point between OC and maximum power points. These features are constructed to detect SC faults under occurring under low mismatch and high impedance which are close to the normal operating conditions. The last two features (F9 and F10), which provide advantages in the detection of OC faults close to the normal operating conditions, refer to the rate of change of conductance at SC point and middle point between, SC and maximum power points, respectively.

Features	Notation	Formulation
F_1	I_{norm}	$I_{MPP}/I_{SC-Array}$
F_2	V_{norm}	$V_{MPP}/V_{OC-Array}$
F_3	FF	$I_{MPP}V_{MPP}/I_{SC}V_{OC}$
F_4	A_{curve}	$\int_0^{V_{OC}} Idl$
F_5	X_s	dI/dV
F_6	X_{s-irr}	$I_{norm}/V_{norm} * irr$
F_7	$\Delta X_s at V_{OC}$	$dI/dV\|_{V_{OC}}$
F_8	$\Delta X_s at mV_{OC}$	$dI/dV\|_{mV_{OC}}$
F_9	$\Delta X_s at I_{OC}$	$dI/dV\|_{I_{SC}}$
F_{10}	$\Delta X_s at mI_{OC}$	$dI/dV\|_{mI_{SC}}$

Table 1. Feature Vectors for Fault Detection

2.2. FEATURE EXTRACTION BY CCA

If all feature vectors are used in the fault detection algorithm, computational complexity will critically increase and affect the efficiency and accuracy of the algorithm. Therefore, CCA is introduced to extract a number of features from high dimensional correlated features.

CCA is a statistical technique used to find the low dimensional linear projections of two maximally correlated high-dimensional random vectors [16, 17]. Let us assume that $\mathbf{F}_i = [F_{i1}; F_{i2}; ...; F_{iN}]^T \in R^n$ is the feature vector, and **Y** is the class label. If there is a main feature $\mathbf{F}_1$ and an auxiliary feature of $\mathbf{F}_2$ of dimension N and $c : R^n \rightarrow \{1,...,M\}$ M classes classifier, providing the $(\mathbf{F}_1;\mathbf{F}_2;\mathbf{Y}) \sim \mathbf{F}_{F1F2;Y}$, be an $R^n x R^n x \{1,...,M\}$ pair, then CCA is applicable on $(\mathbf{F}_1,\mathbf{F}_2)$ pair to derive the projection A based on main $\mathbf{F}_1$ and auxiliary $\mathbf{F}_2$ features. The identification of CCA projection $A = A(\mathbf{F}_1,\mathbf{F}_2)$ can be addressed as the problem of finding two sets of canonical vectors $\{a_i\}$ and $\{a_j\}$ to maximize the correlation between $a_i'\mathbf{F}_1$ and $a_j'\mathbf{F}_2$ for each $i,j = 1,2,...,r$. Dimension reduction for $\mathbf{F}_1$ is obtained from R^n to R^r before a classification operation. Then, a pair of conical vector set is defined as follows.

$$\{a_i, a_j\} = \arg\min \frac{a_i' \sum F_1 F_2 a_j'}{\sqrt{a_i' \sum F_1 a_i} \sqrt{a_j' \sum F_2 a_j}} \quad (1)$$

A matrix is defined as the CCA projection matrix for $\mathbf{F}_1$, and $\mathbf{F}^p_1$ $1 = A'\mathbf{F}_1 \in R^r$ is the projected feature vector. Where $A' = [a_1,..., a]$. Features $(\mathbf{F}_1,\mathbf{F}_3,\mathbf{F}_5,\mathbf{F}_7,\mathbf{F}_9)$ and $(\mathbf{F}_2,\mathbf{F}_4,\mathbf{F}_6,\mathbf{F}_8,\mathbf{F}_{10})$ are determined as main and auxiliary features, respectively.

2.3. RVFLN'S MODEL ESTABLISHMENT

RVFLN which its structure is presented in Figure. 1 is developed as a single hidden layer feedforward network [18]. RVFLN has been successfully used in various engineering practices [19–22] for the purposes of regression and classification since their development. The advantage of RVFLN is the random assignment of weights between the input layer and the hidden layer and the lack of need for tuning. Output weights are calculated with least squares (LS) algorithm. Practically, unlike the gradient-based learning techniques which require the learning parameters to be predefined and training may take several minutes to several hours to ensure the convergence, RVFLN can process data in real-time in most of the engineering applications.

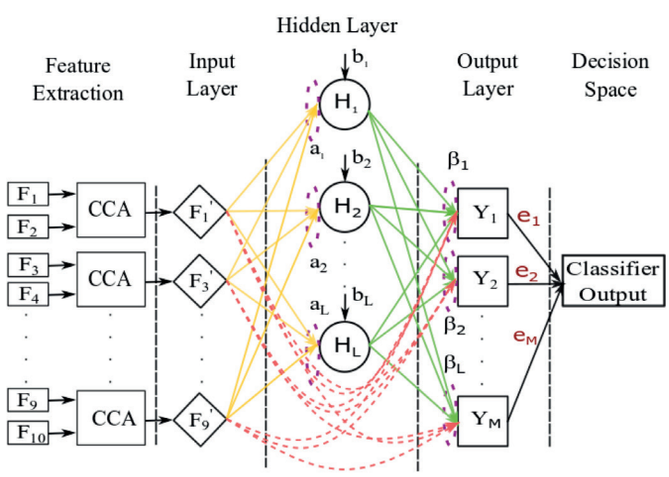


Figure 1. CCA based RVFLNs structure

If $\mathbf{F}^p_i=[F^p_{i1},F^p_{i2},...,F^p_{iN}]^T \in R^n$ and $\mathbf{Y}_i = [Y_{i1}, Y_{i2},...,Y_{iM}]^T \in R^m$ are identified as the input and output vectors, respectively, RVFLN with hidden layer L can be defined as:

$$y_i\left(F_i^P\right) = \sum_{j=1}^{L} \beta_j h\left(\left\langle a_j, F_i^p \right\rangle + b_j\right), i = 1,2,...,M \quad (2)$$

Where $y_i(F^p_i)$ is the output of RVFLN, $a_j=[a_{j1},a_{j2},...,a_{jL}]^T \in R^l$ is the hidden weight vector which connects the input layer and the hidden layer and is generated randomly in a specific probabilistic space, $\beta_j=[\beta_{j1},\beta_{j2},...,\beta_{jM}]^T \in R^m$ is the output weight and must be calculated $b_j=[b_{j1},b_{j2},...,b_{jL}]^T \in R^l$ indicates the bias of hidden node, $\langle a_j,F^p_i\rangle$ refer to inner product of vectors a_j and F^p_i, and for any integrable

$$\int_R h^2(x)dx < \infty \quad (3)$$

or differentiable

$$\int_R \left[h'(x)\right]^2 dx < \infty \quad (4)$$

activation function h(.), there exist a sequence of RVFL $\{y_i\}$ on the probabilistic space of R^L. Some detailed discussions on the activation function can be found in [23]. The learning purpose of RVFLN is to minimize the error between the model outputs and actual outputs by calculating the β_j, a_j and b_j values which satisfy:

$$\sum_{j=1}^{L} \beta_j h(\left\langle a_j, F_i^p \right\rangle + b_j) = y_i, i = 1,2,...,M \quad (5)$$

Which can be compactly defined as:

$$H\beta = Y \quad (6)$$

Where H is the hidden output matrix, β is the output weight matrix that needs to be evaluated and Y is the target output matrix. Those are specifically defined as follows:

$$H(a_1,...,a_L,F_1^p,...,F_M^p,b_1,...,b_L) = \begin{bmatrix} H_1 \\ . \\ . \\ . \\ H_2 \end{bmatrix}$$

$$= \begin{bmatrix} h(\left\langle a_1, F_1^p \right\rangle + b_1) & . & . & . & h(\left\langle a_L, F_1^P \right\rangle + b_L) \\ & & & & \end{bmatrix} \quad (7)$$

$$\beta = \left[\beta_1^T ... \beta_L^T\right]^T, Y = \left[y_1^T ... y_M^T\right]^T$$

After randomly assigning the parameters (a1,...,aL,b1,...,bL) to train the network and find the optimal output weights, functional link networks are trained, and the optimal output weight network $\hat{\beta}$ is obtained with the help of LS by:

$$\hat{\beta} = \arg\min \|H\beta - Y\|^2 \tag{8}$$

Where $\hat{\beta} = \mathbf{H}^{+}\mathrm{Y}$, and $\mathbf{H}^{+}=(\mathbf{H}^{T}\mathbf{H})^{-1}\mathbf{H}^{T}$ is the Moore- Penrose generalized inverse of **H**.

2.3.1. Sparse RVFLN

Sensor error and measurement noise occur in practical applications. We propose to calculate the RVFLN's output weights by sparse-regularization method in order to eliminate the noise and avoid overfitting that may negatively affect the fault detection accuracy. The spare regularization RVFLN includes regularization term, i.e. l2 -norm, in the objective function [24–26] and can be represented by:

$$\hat{\beta} = \frac{1}{2}\|\beta\|_2^2 + \frac{D}{2}\sum_{i=1}^{N}\varepsilon^2 \ \text{ s.t. } y_i = H\beta = \varepsilon_i \tag{9}$$

where *N* is the number of the discrete training samples. Parameter D ensures regularization between $\|\beta\|_2^2$ and the training error and can be computed via Morozov's discrepancy principle [26]. The output weight norm and training error represent the structural and empirical losses, respectively, in (9). In order to improve robustness of the proposed method, NKDE and sparse-RVFLN with loss weighting factor are used. The loss weighting factor can attenuate the effect of noise for both small and long length samples which are also known as the low and high reliability samples, respectively. The long length samples present the normal data while the low length samples include noise. Therefore, we modify (9) as the following:

$$\hat{\beta} = \frac{1}{2}\|\beta\|_2^2 + \frac{D}{2}\sum_{i=1}^{N} q_i \|\varepsilon_i\|_2^2 \tag{10}$$

where q_i is the loss weighting factor for the ith sample, and $\hat{\beta}$ is defines as:

$$\hat{\beta} = \begin{cases} H^T\left(\frac{1}{D} + QHH^T\right)^{-1} QY, & N < L \\ \left(\frac{1}{D} + H^T QH\right)H^T QY, & N > L \end{cases} \tag{11}$$

where q_i is the diagonal element of Θ matrix and $i = 1,..,N$.

We set Θ as the identity matrix and use NKDE to obtain the probability density function for the residuals. A Residual function for sparse-RVFLN can be define as:

$$r_j = \sum_{j=1}^{L}\beta_j h(\langle a_j F_i^p \rangle + b_j) - y_i, i = 1,2,...,N \tag{12}$$

According to (11), the probability density function is represented as:

$$f(x) = \frac{1}{hN}\sum_{j=1}^{n}\phi\left(\frac{x - r_j}{h}\right) \tag{13}$$

where $h = 1.06\sigma N^{-1/5}$ indicates the width of the estimated window, σ represents the standard deviation and φ is Gaussian kernel function which is shown by:

$$\phi(x) = \frac{1}{\sqrt{2}}\exp\left(-\frac{1}{2}x^2\right) \tag{14}$$

Using (13), the probability density function $f(r_j)$ can be calculated for each residual, and Q can be set according to $f(r_j)$. Algorithm 1 shows the implementation of sparse RVFLN for real-time fault detection in PV arrays.

3. CASE STUDIES

In this section, we evaluate the performance of the proposed sparse-RVFLN method for PV fault detection through comprehensive numerical simulation and experiments.

3.1. NUMERICAL SETUP

We implement the PV system in PSCAD/EMTDC and the proposed fault detection method in MATLAB for the numerical simulation. The ungrounded PV array system shown in Fig. 2 consists of 10 PV arrays connected in parallel each of which includes 10 series modules with bypass diodes. To show the performance of our fault detection method, we run the simulation studies for various operating and environment scenarios including different mismatch percentage levels, weather temperatures, irradiation values, and fault instances and impedances. In the following, more details are

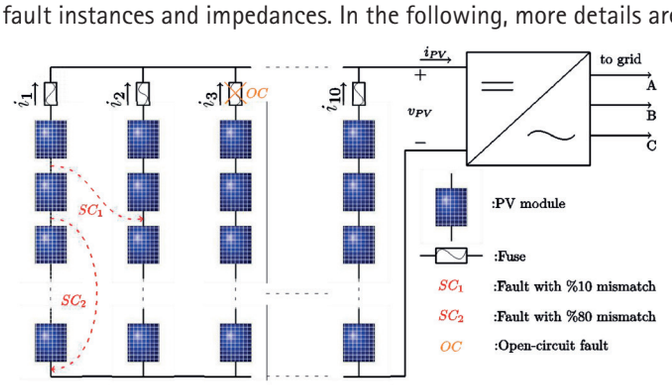


Figure 2. Simulated PV array with potential SC and OC faults

provided for the simulated scenarios.

3.1.1. SC Faults

They are line-to-line (LL) faults occurring under 2250 different conditions. The conditions include a combinations of different fault scenarios such as the irradiation levels (200, 400, 600, 800, 1000) [W/m²], different mismatch percentages (10, 20, 30, 40, 50, 60) %, several temperatures (10, 20, 30, 40, 50) [°C], different fault impedances (0, 5, 15, 25) [Ω], and positive, negative and negative-to positive zero-crossing.

3.1.2. OC Faults

These faults are simulated for 150 different scenarios under the conditions similar to the SC faults. The OC faults are classified into two groups called Group1 and Group2. The former includes The OC faults close to the normal operating conditions, where only one string is faulty at a moment. On the other hand, Group2 includes the OC faults not close to the normal operating conditions, where multiple strings are faulty.

3.1.2. Normal Operating Conditions

To distinguish SC and OC faults from normal operating conditions, the PV system is simulated for 600 different normal operating scenarios under different temperatures, mismatch percentages, fault impedance, and irradiation conditions. The training data set includes 280, 20 and 75 scenarios for SC faults, OC faults and normal operation conditions, respectively.

3.2. SIMULATION RESULTS AND DISCUSSION

Each data set is divided into 75% training data set and 25% test data set. In addition, noise is artificially added to the training dataset to verify the robust performance of the models. For each data set, 30% training sample is randomly selected and a noise whose size is less than 50% of the maximum output value is added. Simulation results of the fault detection algorithm demonstrate the high accuracy of the proposed algorithm. Results are presented in Table 2 for SC faults.

The proposed method has the fault detection accuracy over 95% in cases with 50% or higher mismatch and all fault impedances for SC faults. As the fault impedance increases, and the mismatch percentage decreases, it is quite difficult to detect faults because they are close to normal operating conditions. For instance, in cases of SC faults with less than 30% mismatch and more than 15 fault impedance, the algorithm has a fault detection accuracy of above 55%. On the other hand, the algorithm has the fault detection accuracy of 100% for OC faults which are close to SC faults and normal operating conditions (e.g. OC fault in one string), and OC faults occurring in multiple strings. The results of fault detection accuracy assessment in OC fault scenarios are given in Table 3.

Figure. 3 and 4 show the SC and OC fault detection accuracy of the proposed method in comparison with LS-SVM and LSRVFLN methods. According to the results, sparse RVFLN has a better detection accuracy for both SC and OC faults owing to calculating the output weights of RVFLN by sparse estimation method.

3.2.1. SC Faults with Blocking Diodes

In this subsection, the performance of the proposed method is evaluated for the scenarios with SC faults where each PV string has a blocking diode. In this case, we do not repeat the training and parameter-setting processes. The results given in Table 4 demonstrate that the proposed algorithm detects all SC faults with more than 30% mismatch and less than 15 fault impedance.

3.2.2. SC-OC Faults With Noisy Measurements

To test the robustness of the proposed method against noisy measurements, the samples are selected randomly at the ratios of 5%, 15%, 25%, 35% and 45% from the training dataset, and the noisy dataset is generated. detection accuracy results including noisy measurement are given in Table 5 for SC and OC faults. The results show that fault detection accuracy of the other methods decreases dues to the noisy measurements, while sparse-RVFLN provides an acceptable detection accuracy for both SC and OC faults.

Mismatch Percentage(%)	Fault Impedance[Ω]				Average Accuracy(%)
	0	5	15	25	
60	100	100	96.7	91.5	97.1
50	100	98.9	92	90.3	95.3
40	97	95.4	76	74.2	85.7
30	92.4	88.2	70.5	74.2	77.8
20	88.8	73.7	52.2	47.3	65.5
10	74.3	53.5	46.4	40.3	53.6

Table 2. Simulation Results for the Simulated SC Faults

Group#	Temp[°C]	Irradiance[W/m2]					Average Accuracy(%)
		200	400	600	800	1000	
1	10	100	100	100	100	100	100
	20	100	100	100	100	100	100
	30	100	100	100	100	100	100
	40	100	100	100	100	100	100
	50	100	100	100	100	100	100
	60	100	100	100	100	100	100
2	10	100	100	100	100	100	100
	20	100	100	100	100	100	100
	30	100	100	100	100	100	100
	40	100	100	100	100	100	100
	50	100	100	100	100	100	100
	60	100	100	100	100	100	100

Table 3. Simulation Results for the Simulated OC Faults

Fault Types	Mismatch Percentage	Fault Impedance			
		0	5	15	25
L-L FaultS	60	Y	Y	Y	N
	50	Y	Y	N	N
	40	Y	Y	N	N
	30	Y	N	N	N
	20	Y	N	N	N
	10	Y	N	N	N

Table 4. Simulation Results for SC Faults with Blocking Diode

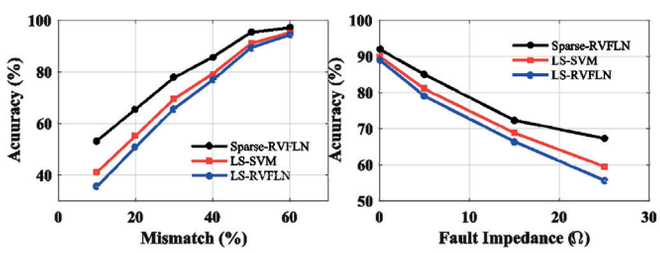


Figure 3. Comparison of SC fault detection accuracy by Sparse-RVFLN, LS-SVM, and LS-RVFLN

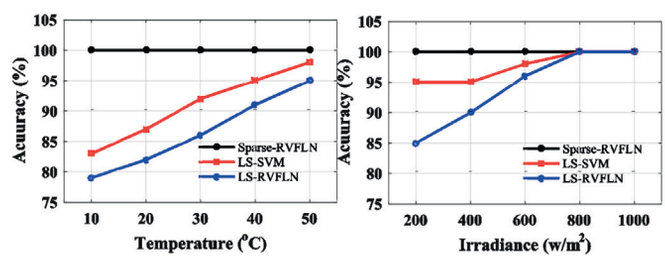


Figure 4. Comparison of OC fault detection accuracy by Sparse-RVFLN, LS-SVM, and LS-RVFLN

Fault Type	Method	Average Accuracy(%)	
		Noisy	Noiseless
SC	RVFLN	60.4	70.2
	Sparse-RVFLN	77.3	79.1
	LS-SVM	65.7	73.6
OC	RVFLN	83	89.1
	Sparse-RVFLN	98	100
	LS-SVM	86.2	91.4

Table 5. SC-OC Fault Detection Accuracy with noisy measurement

3.2.3. Comparison of Computational Efficiency

Assigning input weights randomly and calculating the output weights without training, which is required by the conventional algorithms enable RVFLN to process and learn data fast which is suitable for practical application. Comparison of the proposed method and other conventional methods is presented in Table 6.

Method	Training Time(sec)	Testing Time(sec)
RVFLN	0.0125	0.0035
Sparse-RVFLN	0.1257	0.0045
LS-SVM	0.7264	0.9345

Table 6. Comparison of Computational efficiency

3.2.4. Comparison with Previous Studies

In the literature, method for detecting SC faults assume only one of the parameter such as PV module mismatch, fault impedance, irradiance, and temperature that affects characteristic of faults as variable, while the others are kept constant, in this study mismatch percentage (*10,20,30,40,50,60%*), Fault impedance (*0,5,15,25*Ω), irradiance (*200,400,600,800,1000W/m²*), temperature (*10,20,30,40,50°C*) are considered as variable. For example, in [2,14] only mismatch percentage (*20% and 50%*) and fault impedance (*0 and 20*Ω) values are taken into account, while irradiance(*1000W/m²*) and temperature(*25°C*) are constant. Compared to [2,14], this study provides a higher detection accuracy for hard to detect SC faults that are with *20%* mismatch percentage and *20*Ω fault impedance. In addition, in this study OC faults are also considered, unlike SC faults detection studies that take into account variable mismatch percentage, fault impedance, irradiance and temperature values in the literature. It is difficult to detect some OC faults, especially that are closed to normal operation and hard to detect faults with *10%* mismatch percentage and *25*Ω fault impedance. Although this study has taken into consideration of OC faults, compare with [12,13] it has a higher fault detection accuracy under condition of low mismatch (*10%*) and high fault impedance(*25*Ω).

3.2. EXPERIMENTAL VERIFICATION AND DISCUSSION

A small-scale grid-connected PV array shown in Fig. 5 is set up to verify the performance of the proposed algorithm. Each PV array includes 4 panels connected in series and 10 in parallel. The parameters values of the experimental setup under standard test conditions(STC) are as follows: ISCSTC= 200 [mA], VOCSTC = 6 [V], 40 polycrystalline-silicon panels, central grid-connected inverter 300 [W] DC input 12.5-28 [V], AC output 120-280 [V] and a DQA board.

Simulations of SC faults for a total of 240 different cases including different temperatures, irradiations, fault impedances (0, 5, 15, 25), and mismatches percentage (10, 30, 60%) are performed. On the other hand, 60 different cases are performed for

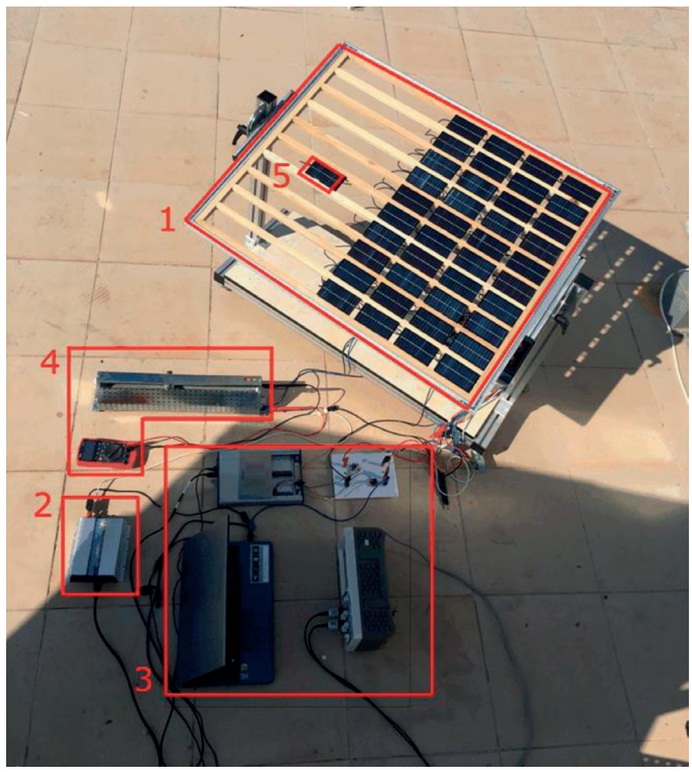


Figure 5: Grid-connected PV array for experimental setup: (1) PV array, (2) inverter, (3) data acquisition & processing hardware, (4) fault impedance, and (5) reference module for irradiance

OC faults. Table 7 and Table 8 show the detection accuracy of SC and OC faults, respectively. According to the results, the algorithm can detect at least 12 out of 20 SC faults with 30% mismatch, and for all fault impedances and minimum 18 out of 20 faults in cases with more than 30% mismatch. On the other hand, it detects 30 out of 30 faults in OC faults for Group1 which are close to normal

Mismatch Percentage(%)	Fault Impedance[Ω]				Average Accuracy(%)
	0	5	15	25	
60	20/20	20/20	19/20	18/20	96.5
30	18/20	17/20	14/20	12/20	77.5
10	14/20	10/20	9/20	8/20	51.3

Table 7. Experimental Results for SC Faults

Fault Types	Temp [°C]	Irradiance(W/m²)			Average Accuray(%)
		200-300	300-400	500-600	
1	30-45	10/10	10/10	10/10	100
2	30-45	10/10	10/10	10/10	100

Table 8. Exprimental Results for SC Faults

operating conditions and also 30 out of 30 faults in Group2 OC faults.

3. CONCLUSION AND FUTURE WORK

Some photovoltaic faults have a small fault current due to low irradiance conditions and active maximum PowerPoint tracking algorithm, so they may not be detected by overcurrent protection devices. Therefore, faults can remain hidden in the photovoltaic system, which can lead to potential hazards (performance degradation, fire hazard, etc.). To identify SC and OC faults under such conditions, for the first time a new sparse-RVFLN method has been proposed. It is aimed to increase the safety and reliability of the PV

Array. To implement sparse-RVFLN, new features are constructed and transformed by CCA to lower the dimension space and improve fault detection accuracy for hard to detect fault conditions such as low mismatch, high impedance, and active MPPT. Also, sparse-regularization is used to calculate RVFLNs output weights to minimize the effect of measurement noise and overfitting on the detection accuracy. Furthermore, the PV arrays have different inverter types and topologies in real time applications, the proposed method can be easily applied to any PV array, regardless of the inverter type and topology, since the measurements (current, voltage and irradiance) used in the method are available for all inverter types and requiring no additional hardware installations.

The performance of the proposed method is verified by both simulation and experimental setup. In SC fault scenarios with low mismatch and high impedance fault, which are close to normal operating conditions, the proposed method provides a detection accuracy of minimum 77.5% for 30% low mismatch and all fault impedances, while it results in a detection accuracy of 100% in all OC fault scenarios. The proposed spare-RVFLN method is also compared with the conventional RVFLN and LS-SVM. The measurements with noise, in particular, reduce the fault detection accuracy of LS-SVM and RVFLN while it does not degrade the sparse-RVFLN performance. Furthermore, sparse-RVFLN has a higher computational efficiency than the conventional RVFLN and LS-SVM.

Notwithstanding the fact that the DC-side faults in PV arraysare investigated in this paper, numerous other faults occur in PVsystems including ground SC, partial shading, arc and hot-spot faults.Therefore, we will focus on the development of the algorithmsenabling the detection of those faults in our future research.

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