Diagnosis and Classification of Photovoltaic Panel Defects Based on a Hybrid Intelligent Method

Saliha Sebbane, Noamane Ncir, and Nabil El Akchioui

Abstract To enhance the efficiency of the energy generated by a photovoltaic system (PV), a control and monitoring system must be included in the PV system to guarantee that faults are recognized instantly. With the appearance of artificial intelligence-based methods, including machine learning (K-nearest neighbor (k-NN), Decision Tree (DT), Support Vector Machine (SVM), and Artificial Neural Network (ANN)). And through the evaluation of these methods in the classification of photovoltaic faults, the results show that the ANN performs better than other machine learning approaches on the classification of solar field defects. However, due to the artificial neural network's slow learning phase convergence, this article proposes a hybrid diagnostic method based on particle swarm optimization and the neural network (PSO-ANN) to improve the accuracy and the convergence speed of an ANN. To compare the performance of ANNs with the PSO-ANN method, the solar generator's current Ipv and voltage Vpv characteristics are used as identification parameters.

Keywords Photovoltaic system · Fault classification · Artificial intelligence (AI) · Artificial neural network (ANN) · Particle swarm optimization (PSO)

1 Introduction

To ensure a sustainable source of energy, Morocco has adopted a national strategy on renewable energies to reduce the use of fossil fuels. The strategy includes increasing solar energy potential to 5000 MWc in 2030 [1].

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This policy was accompanied by the intense use of photovoltaic systems (PV) at the national level because of its many advantages. However, PV installations are sudden from time to time failures resulting in a decrease in the electricity produced, which is why a lot of research is devoted to developing diagnostic techniques for PV fields to guarantee reliable And efficient power output.

The diagnostic methods are divided into two categories, the first category contains conventional methods described in literature and industry [2–5], and the second category contains methods based on artificial intelligence (AI) [6]. The research results prove that the artificial neural network (ANN) is the best solution to overcome the limitations of traditional methods and other machine learning methods in the accuracy of detection and identification of defects [7]. However, there is a problem during the use of ANNs to detect and classify faults, such as the slow convergence in the learning phase, which requires performance optimization of ANN.

In this study, the artificial neural network was optimized using a metaheuristic algorithm, to improve diagnostic accuracy and minimize learning time. It is a hybrid diagnostic method based on particle swarm optimization (PSO) and neural network (PSO-ANN). In this article, the first part presents the studied PV field defects, the second and third parts are about the details of the ANN and PSO methods, and the fourth part deals with the combination between the ANN and the PSO method. Finally, the results obtained by ANN are discussed and compared with those of PSO-ANN.

2 Defects of a Photovoltaic Field

A change in the operating conditions of the PV array indicates implicitly that a fault has occurred. This fault can be divided into three categories [8]: physical faults can be a cracking or degradation of photovoltaic modules, such as corrosion and oxidation, the second category are electrical faults which are: open-circuit, short-circuit, and environmental faults include shading and dirt caused by accumulated dust, bird drops and snow.

In this article, the classification is done on three faults which are: partial shading fault, short-circuit fault, and open-circuit fault, as long as these three faults commonly appear and occur in the PV field.

2.1 Partial Shading

Partial shading is the act of obstructing solar radiation from reaching a part of the photovoltaic module contained in a PV field. While a part of the photovoltaic module is exposed to partial shading, and the other part is fully exposed to solar radiation, the output current of the photovoltaic generator is reduced, which leads to the reduction of the total power produced by the PV field.

2.2 Short-Circuit Fault

The short-circuit fault produced in a PV field is mainly due to the infiltration of water in the modules, bad wiring between the module and the inverter, or the aging of the PV modules, due to the functioning in long-term of PV system [9].

When a PV module is short-circuited, the voltage is zero. The current in the field becomes equal to the maximum current produced by the modules, and the short-circuited path carries the excess current.

2.3 Open-Circuit Fault

An open-circuit fault occurs due to a break in the connection wires between the PV cells. This type of fault is usually caused by the poor quality of the connections between PV cells, through the manufacturing process, especially when one of these high resistance connections occurs.

3 Artificial Neural Network (ANN)

Artificial neural networks are mathematical models inspired by biology. As the basic rebels of these networks, artificial neurons were originally the result of the hope to model the function of biological neurons, which can be divided into three major entities: a cell body, a set of dendrites, and an axon [10].

Perceptrons also called artificial neurons or formal neurons, are designed to mimic the functions of biological neurons [11]. Therefore, there are several levels of abstraction, depending on the precision of the modeling as shown in Fig. 1.

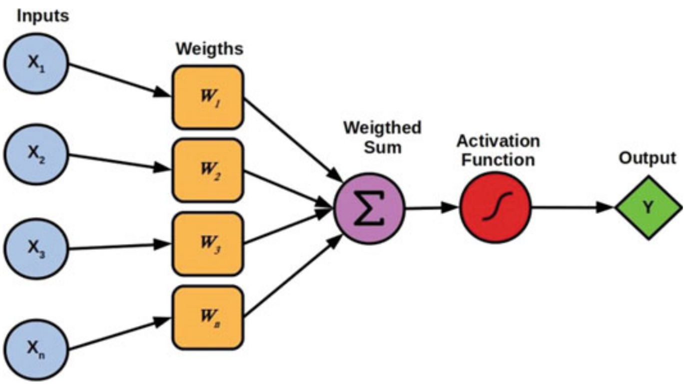

Fig. 1 Representation of an artificial neuron

From the figure above, we will consider the following entities:

- Entries labeled in vector form, representing dendrites.
- A noted output representing the axon.
- The parameters noted w and b affect neuronal function.

This representation can be modeled as an Eq. (1) that shows how to calculate the output by multiplying the input by the weight then adding them to the bias. Finally, the result of the summation goes through the transfer function f, which is generally nonlinear.

$$\hat{y} = f(\langle \omega, x \rangle + b) \tag{1}$$

The growing complexity of the problem makes it very difficult to resolve. That is why a single neuron cannot cope with complex problems. So the effective method that allows solving such a problem is to assemble several perceptrons to obtain what is called the multilayer perceptron (MLP), which is an early-acting ANN and can be applied in several applications such as recognition of images, shapes or speech, prediction, etc. [12].

MLP is suitable for fixed-size data, such as images, and can contain at least three main layers, the input layer, the hidden layer, and the output layer. In other words, information flows from the input layer to the output layer via the hidden layer to decrease the error between the desired output and the measured one. This error is calculated with Eq. (2).

$$J(a) = \frac{1}{2m} \sum_{i=1}^{m} \left(y_i - \hat{y}_i\right)^2 \tag{2}$$

4 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a stochastic optimization metaheuristic proposed by Eberhart and Kennedy in 1995 [13]. PSO is an optimization algorithm inspired by biologies such as the artificial neural network, genetic algorithms, or ant colony algorithms. It simulates the social behavior and movement of animals (insects, birds, and fish, etc.) in search of food [14].

In this method, the swarm is randomly initialized in the search space. The members of the swarm move (according to Eqs. (3) and (4) [15], and interact with each other to reach the best area of solution space. Each particle resides in a place in the search space, then passes to the evaluation with a fitness function to know the quality of its position.

$$V(t+1) = V(t) + C_1 r_1 (\mathrm{Pb}(t) - X((t)) + C_2 r_2 (\mathrm{Pg}(t) - X(t)) \tag{3}$$

```
Initialize initial position Xi, initial velocity Vi, Pb, Pg ;
Generate random particles (P) ;
for each particle (Pi)
        Calculate the new velocity using the equation (3);
        Calculate a new position using the equation (4);
        Calculate the fitness value of each particle (Pi);
        If f(Pi) is better than f(pb) then
                Pb = Pi;
        If f(Pb) is better than f(Pg) then
                Pg = pb;
End for
```

Fig. 2 Pseudo code of PSO algorithm

$$X(t+1) = X(t) + V(t+1) \tag{4}$$

X	the position of the particle in the search space;
V	the velocity of the particle;
Pb	the position of the best solution through which the particle has passed;
Pg	the position of the best known solution of the whole swarm;
C_1 and C_2	acceleration coefficients;
r_1 and r_2	two random numbers in the interval [0,1].

The conventional algorithm of the PSO method begins with the initialization of the initial population (N), position, and velocity of movement. The particles move in each iteration using Eqs. (3) and (4), and the fitness function of each particle in the swarm is calculated to indicate the best position of the whole population (Pg).

After the evaluation of the fitness function value, Pb and Pg are updated, this procedure is repeated until the stop criterion is reached. The pseudo-code of the PSO is cited in Fig. 2 [16].

5 PSO-ANN

5.1 Design of the PSO-ANN Hybrid Method

ANNs are characterized by the efficiency of detection and diagnosis of almost all faults affecting the PV field [17]. ANN effectiveness refers to the value of weights and biases, but when using the ANN-based diagnostic model, convergence is slow in the training step.

This study proposes a hybrid diagnostic method based on particle swarm optimization and artificial neural network (PSO-ANN). The goal of using PSO is to optimize the ANN in terms of convergence and accuracy.

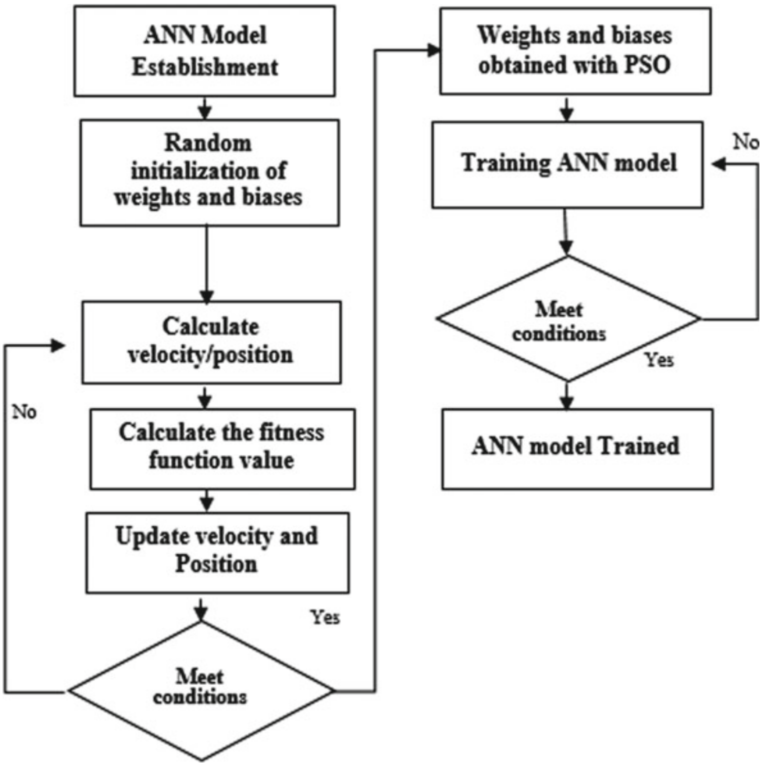

Fig. 3 Flowchart of the PSO-ANN hybrid method

In the PSO-ANN model, each position contains the initial weights and biases, weights and biases are optimized before the learning phase, then used to build the network, and next optimized again in the training step by minimizing the objective function. Figure 3 shows the flowchart of the PSO-ANN model.

5.2 Methodology

The methodology adopted in the present study is composed of two steps: the first step involves collecting the data used to train the neural network, while the second step determines the neural network structure used for defect classification. To collect the data necessary for training the neural network, a PV field (4 modules in series, 4 in parallel) is simulated on MATLAB/Simulink, under standard test conditions, and different fault conditions presented previously.

The data assembled in this process for fault identification are the current Ipv and the voltage Vpv generated by the PV field, including 331,315 samples.

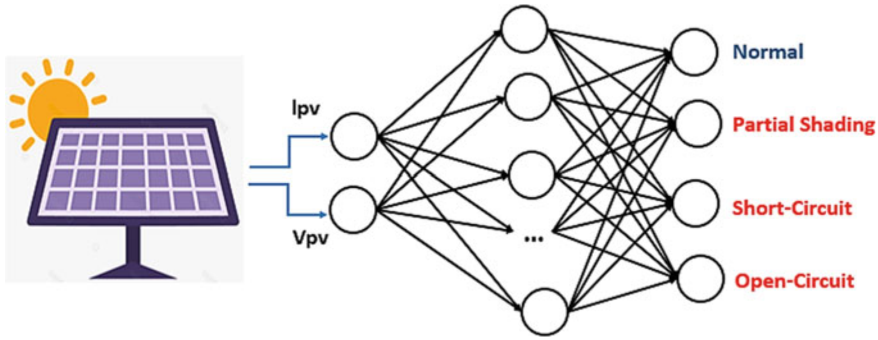

Fig. 4 Schematic diagram of proposed PSO-ANN method to detect the state of PV Field

Concerning the neural network structure used in the diagnostic model, we used a 3-layer neural network, the input layer contains two neurons that receive the current Ipv and the voltage Vpv, the hidden layer containing ten neurons, finally, the output layer composed of four neurons, each one presents the state of the PV field, such as a normal functioning or a type of fault (partial shading fault, short-circuit fault and open circuit fault). Figure 4 shows the simulation model diagram used to identify the state of the PV field.

5.3 Result and Discussion

In this article, we performed a neural network-based diagnostic model. The neural network structure chosen in this work is the MLP with three layers. The latter was trained first with four training algorithms, including Gradient Descent (GD), Levenberg–Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG), to determine which is the correct one, which gives the small error compared to other algorithms. We have chosen the sigmoid tangent function as the activation function to obtain the output results as probabilities between -1 and 1. The objective function used in the diagnostic model and the mean squared error (MSE) (shown in Eq. 2). The results of training the ANN with the four algorithms are given in Table 1.

Table 1 The results of training the neural network with the four training algorithms

Algorithm	Iterations number	Error (MSE)	Accuracy (%)
GD	183	0.0945	90.55
LM	449	0.0010	99.89
BR	639	0.0013	99.87
SCG	957	0.0371	96.29

We note from Table 1 that the Levenberg–Marquardt (LM) algorithm shows better accuracy in comparison with gradient descent (GD), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG). With the results cited in [18–20], we can also observe that the LM algorithm offers better results in the diagnosis of faults in the photovoltaic field.

The previous results will be taken into account to fix the learning algorithm, the next step is the training of the neural network with PSO-ANN with Levenberg–Marquardt (LM). The PSO parameter values are shown in Table 2.

The PSO-ANN model is trained with the same 331 315 samples collected in the data collection process, where 70% of the data is designated for the learning stage of the ANN, 15% is used in the validation step, while the remaining 15% is used in the learning test step. The simulation result is shown in Fig. 5.

From the analysis of Fig. 5, we notice that the PSO algorithm plays a crucial role in the performance optimization of ANN. With the PSO-ANN model, the learning step is accomplished with less iteration (365) in comparison with the ANN model (449), which means that the PSO-ANN converges faster than the ANN model. The

Table 2 The values of the important parameters of PSO

Parameters	Symbol	Value
Population	N	25
Max iteration	Tmax	100
Cognitive factor	C_1	1.5
Social factor	C_2	2.5

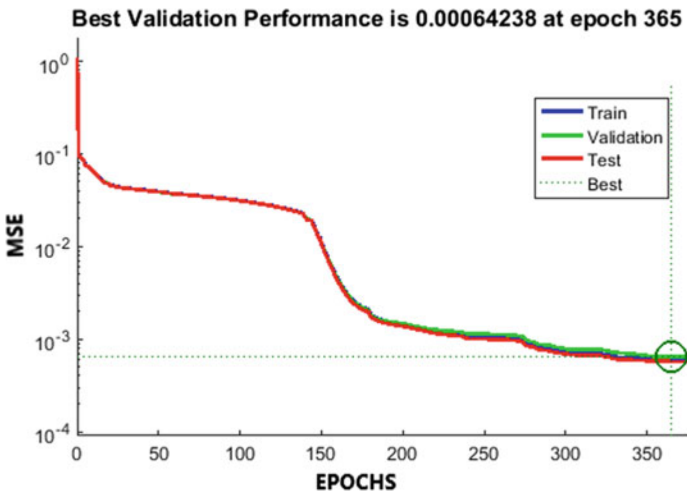

Fig. 5 The mean squared error of PSO-ANN model

Table 3 The classification results of the PSO-ANN model

State of PV field	Scenarios	Predicted result			
		N	PS	SC	OC
Partial shading (PS)	Irradiation of the first column = 800 W/m^2	0.0199	**1**	−0.001	−0.001
Normal (N)	Under standard test condition Irradiance = 1000 W/m^2	**1**	−0.037	0.005	−0.005
Short-circuit (SC)	Two modules are short-circuited	−0.0159	0.020	**0.9966**	−0.0013
Open-circuit (OC)	Four modules are disconnected	0.115	−0.106	−0.006	**1**
Open-circuit (OC)	Six modules are disconnected	0.030	0.146	0.046	**0.7773**
Short-circuit (SC)	Only one module are short-circuited	0.008	−0.010	**1**	0.000
Partial Shading (PS)	Irradiation of the first line = 500 W/m^2 and Irradiation of three modules in the first column = 500 W/m^2	−0.0009	**0.66**	0.039	0.296

classification precision of the hybrid method reaches a value of 99.94% though the model precision ANN reaches just 99.89%.

Reference [21] proposed a meta-heuristic method based on the PSO and the neural network for diagnosing the photovoltaic field. The results of this reference and the results obtained in our article prove that the diagnostic model obtained in our research is more precise and the training of the model requires only two inputs and necessitates fewer populations and fewer iterations for the parameters of the PSO algorithm.

The trained model based on PSO-ANN is tested under several states of the chosen PV field, the states are assembled between the three defects and the case of normal functioning. The results are shown in Table 3.

6 Conclusion

In this research, we have combined the metaheuristic optimization algorithm PSO and the artificial neural network ANN. This combination aims to reduce the convergence time of the artificial neural network and thus improve the accuracy of the classification.

The proposed PSO-ANN model is trained with current Ipv and voltage Vpv. These parameters are obtained by simulating the PV field using “Matlab Simulink” in several cases. The results show that the PSO-ANN model achieves an accuracy of 99.94% in fewer iterations than the ANN-based diagnostic model.

The diagnostic model based on the hybrid method was tested on a PV field under several faults to determine its capacity. The results prove that the fault identification is done correctly with good precision, which offers an accurate diagnostic model.

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