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A Novel Hybrid Method Based on Fireworks Algorithm and Artificial Neural Network for Photovoltaic System Fault Diagnosis

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Abstract- In the last years, the need for robust photovoltaic systems has been escalated, which has been involved the high accuracy and the robustness of the diagnostic systems, whether at a normal run or when facing unexpected events. Therefore, the diagnostic systems must stick strictly to the security- or safety-criteria of the system components and humans, while strengthening their ability to improve the efficiency of the produced energy. Recently, the research has been focused mainly on the development of an intelligent diagnostic system characterized by precision, stability, and speed. In this article, a new diagnostic system is based on the Artificial Neural Network (ANN) and the Evolutionary Fireworks Algorithm (FWA) has been proposed. The method proposed in this article combines the prediction of two different algorithms to obtain more satisfactory accuracy, the objective of hybridization is to optimize the artificial neural network in terms of precision and convergence. The state of the photovoltaic field is determined by the diagnostic model, based on the voltage and current delivered by the field in real-time to make the diagnostic assignment uncomplicated and more reasonable. Our novel hybrid model FWA-ANN has defeated the PSO-ANN model in terms of high accuracy and reduced time of convergence by less than a half, which has proved that our proposed method is a promising model for Neural Network optimization for the PV field compared to the previous works. The results in this study prove that the hybrid method achieves an accuracy of 99.98% in 241 iterations compared to the ANN model which reaches only 99.94% in 682 and the PSO-ANN model which achieves 99.95% accuracy in 564 iterations.

Keywords Photovoltaic field; artificial intelligence; metaheuristic algorithms; evolutionary algorithms, artificial neural network; Fireworks Algorithm; particle swarm optimization.

1. Introduction

Renewable energy technology advancement for the last decade and the largest scope of its applications and research, that has made a major contribution to achieving local and global climate change alleviation, and fossil fuels preservation, by switching to alternative sources such as solar energy. Photovoltaics (PV) has been gained tremendous interest by numerous researchers. Hence, many novel technologies were aimed to develop robust diagnostic systems that have combined safety, sustainability, and reliability. Photovoltaics (PV) systems undergo constant evolution to ensure the highest accuracy and efficiency, therefore the use of Artificial Intelligence AI systems based on neural networks to tackle the major issues for PV, the precision level, and the convergence time. The diagnostic systems based on ANN have tremendously increased their performance over the course of the last years.

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 5,000 MWp by 2030 [1]. This policy was accompanied by the intense use of photovoltaic (PV) systems at the national level grace with its many advantages. Therefore, the use of photovoltaic systems has been grown very rapidly in recent years. However, the power generated by these systems has been increased by 2.9%. Nevertheless, the significant increase, PV is known to be suffering from energy-loss, manifested in a decrease of its produced electricity, resulting from the installations failures, which requires diagnostic and monitoring systems to operate these installations on a large scale, therefore, a lot of research have been devoted to developing diagnostic techniques to ensure energy efficiency, personal safety, and increase reliability.

Various diagnostic techniques can be divided into two broad categories, the first category has contained conventional methods described in literature and industry [2-5], and the second category has used methods that are based on AI [6]. Research results have proved that traditional diagnostic methods offer the possibility of detecting and locating faults very finely with greater precision, but they are inefficient in detecting all faults involving photovoltaic systems, and in distinguishing faults in real-time.

On the other hand, in the second category of diagnostic methods, artificial neural networks (ANNs) were found to be highly exploited in the energy field [7-8] as well as in the photovoltaic field, and their reliability is demonstrated in the estimation and prediction of solar irradiance [9-12], the maximum power point tracking [14-16], reconfiguration process in photovoltaic (PV) arrays [18], as well as in the diagnosis and control of photovoltaic installations [19-28]. The use of neural networks as an intelligent diagnostic model in most research has justified that they are the best solution to solve the limitations of traditional methods and other machine learning methods regarding the accuracy of photovoltaic defect detection and identification [29].

Due to the intense use of neural networks in the diagnosis of PV systems, especially in the PV field, it seems that the ANN is facing a problem in the learning phase and they are trained using large data sets, which leads to a slow convergence by taking a long time to minimize training error and therefore a low predictive or classification accuracy. Recently, several studies have been proposed to optimize neural networks with optimization algorithms to overcome the problem of low convergence, and to improve the error minimization process. In [30] the ANN is combined with the firefly Algorithm (FA), in [31] a hybrid method based on the ANN and the Particle Swarm Optimization algorithm (PSO) is used to diagnose the PV system, the ANN is combined in [32] with Grey Wolf algorithm (GWO), Ant Lion algorithm (ALO) and whale Optimization Algorithm (WOA) to predict daily the power produced by the PV system. In the present work, our motive is to propose a novel solution based on neural network hybridization and optimization algorithms to minimize the learning time and improve the accuracy of the diagnostic model. In this study, the artificial neural network was optimized using an optimization metaheuristic. It is a hybrid diagnostic method based on the Evolutionary Fireworks Algorithm (FWA) and the neural network.

The proposed hybrid diagnostic model is training using two inputs, the current and voltage supplied by the PV field in real-time. That facilitates the diagnosis of the PV field since these two parameters are accessible compared to other parameters such as the short-circuit current, the open-circuit voltage, and the maximum power point, these parameters require a precise process for the results obtained such as the method for extracting the characteristic of the curve I-V of the field PV. The objective of the proposed method is to have a fast and accurate intelligent diagnostic model that works in real-time and with fewer parameters.

In this article, the first section presents a preface on neural networks, and a detailed overview of the fireworks algorithm and its steps. The key idea of the hybridization between the ANN and the FWA algorithm will be emphasized and elaborated in the third section. Finally, the results obtained by ANN will be discussed and compared with those of FWA-ANN to verify the effectiveness of our proposed hybrid method.

2. Introduction of Artificial Neural Network and Fireworks Algorithm

2.1. Artificial Neural Network (ANN)

Artificial neural networks are mathematical models inspired by biology in general, they try to mimic the behavior of real-life neurons, since the biological neural network is the main constituent that is responsible for all work in the human body [33].

Mathematical modeling of a biological neuron is given us what is called the perceptron, also called artificial neuron or formal neuron. This modeling is designed to mimic the functions of biological neurons and the functioning of the human brain. The artificial neuron diagram is shown in Fig.1.

The representation of ANN can be modeled as equation (1), which shows how to calculate the output by multiplying the input (x) by the weight (w) , then adding them to the bias (b) . Finally, the result of the summation goes through the transfer function f, which is generally nonlinear.

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

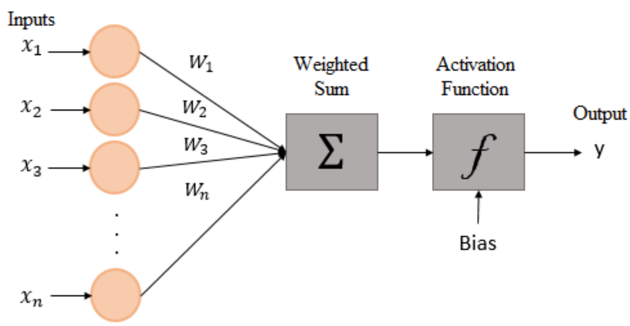

Fig. 1. Representation of an artificial neuron.

With the increasing complexity of the problem, solving these problems will be sophisticated because a single neuron is unable to solve this type of problem. Hence the fact of bringing together several perceptrons to obtain what is called a Multilayer Perceptron (MLP) which is an early-acting ANN. Mainly, to bunch of these perceptrons together to create a reliable and powerful mechanism for learning, which can be applied in several advanced applications such as prediction, image recognition, recognition of shapes or speech, etc.

2.2. Fireworks Algorithm (FWA)

Fireworks Algorithm (FWA) is one of the evolutionary algorithms developed in 2010 [34]. The FWA algorithm is referred to as using the explosion of real fireworks as a search space to achieve the best value of the optimization function. FWA has been seen widely used in various fields overcoming optimization issues such as optimizing settings for spam detection, reconfiguring networks, and designing digital filters [35].

Reproducing the operation of the firework explosion is done by following the steps shown in Fig.2, first, the fireworks are positioned in N locations, the second step is the explosion of the fireworks to obtain the sparks, and then they are evaluated to find the best location, when it is found, the algorithm will be stopped. Otherwise, N other locations will be chosen from the recent sparks and fireworks for the explosion of the new generation.

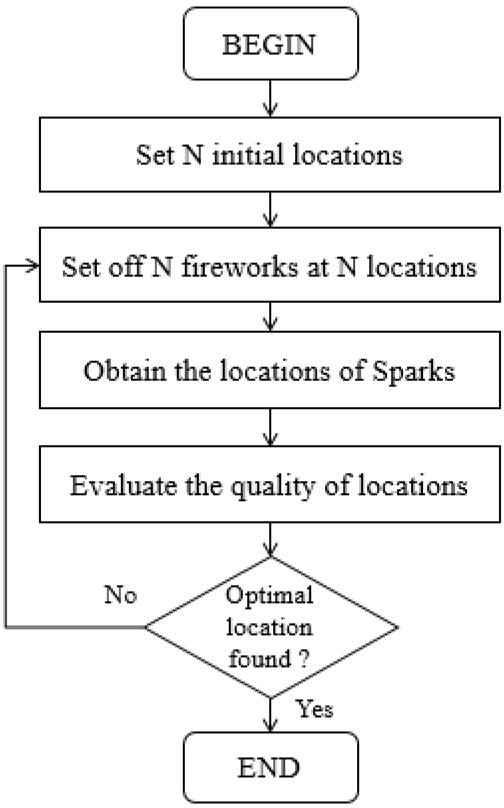

Fig. 2. Flowchart of FWA algorithm.

➢ Explosion Operator

After the explosion, fireworks will be represented in the form of two attitudes. As shown in Fig.3, the first attitude is characterized by the production of a good firework, containing many sparks gathered around the center of the explosion which is favored the search in-depth in restricted area. However, the second attitude was characterized by a bad explosion of fireworks, where there are fewer sparks generated in the search space, which is given a better ability to explore the search space.

The number of sparks generated after the explosion of fireworks is calculated with equation (2), while equation (3) is used to calculate the explosion amplitude and to balance the many sparks that have been produced by the good fireworks and those by the bad fireworks, equation (4) is applied to limit the number of sparks that have been generated after the explosion of the firework [36].

$$S_i = m \times \frac{Y_{max} - f(x_i) + \varepsilon}{\sum_{i=1}^{N}(Y_{max} - f(x_i)) + \varepsilon} \tag{2}$$

$$A_i = A \times \frac{f(x_i) - Y_{min} + \varepsilon}{\sum_{i=1}^{N}(f(x_i) - Y_{min}) + \varepsilon} \tag{3}$$

$$S_i = \begin{cases} round(a.m) \text{ if } S_i < am, \\ round(b.m) \text{ if } S_i > bm, \\ round(S_i) \quad otherwie. \end{cases} \tag{4}$$

Where:

- Si and Ai are respectively the numbers of sparks generated for and the explosion amplitude.
- m and A are constants used to control the total number of sparks
- Ymax = max (f(x)) and Ymin = min (f(x)) are respectively the worst and the best value of the objective function of the firework xi,
- ε is used to prevent the denominator from becoming zero.
- a and b are two constants which limit the number of sparks.

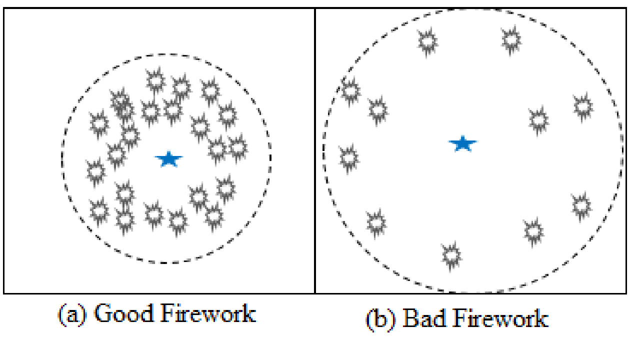

Fig. 3. Types of Fireworks explosion.

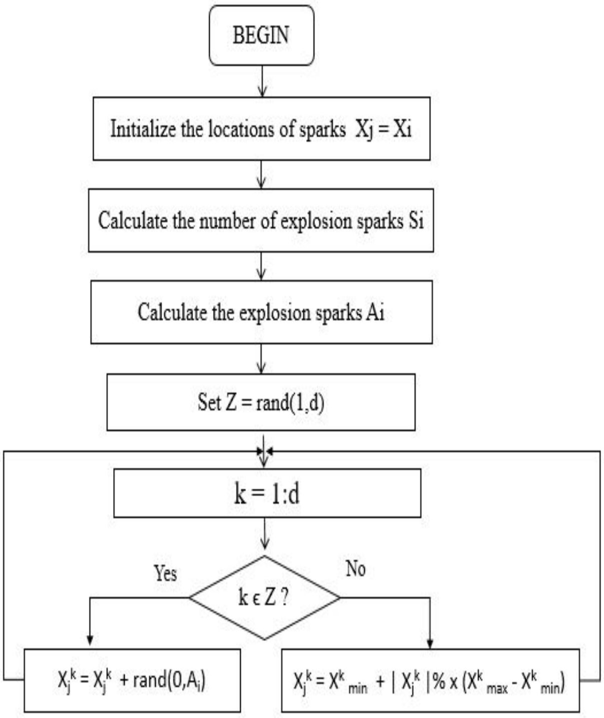

Fig.4. Flowchart of explosion operator.

After the generation of explosive sparks, they are directed randomly into the research space using equation (5).

$$Z = \text{round}\ (\text{d. rand}\ (0, 1)) \tag{5}$$

Where d is the dimension of the search space and rand (0.1) is a uniformly distributed random number in the interval [0.1]. The generation and location of fireworks and sparks in the search space are obtained by Fig.4.

- Mutation Operator

The mutation is an operator to introduce new characteristics that do not exist in the population. The mutation operator of the FWA algorithm has made it possible to design another type of sparks called Gaussian sparks to increase and ensure the diversity of the population. The generation of sparks with the Gaussian mutation operator is shown in Fig.5. The principle of this operator is to add a Gaussian distributed random value to rule out the solution from falling into the local extreme values [37].

- Selection of Locations Operator

Fireworks, sparks, and Gaussian sparks are evaluated by examining their fitness function. The individual who has the best current value of the objective function is saved for the fireworks explosion in the next iteration [34], then the remaining N-1 locations are chosen, based on their distance and probability which are calculated by equation (6) and equation (7).

$$R(X_i) = \sum_{j \in K} d(X_i, X_j) = \sum_{j \in K} \| X_i - X_j \| \tag{6}$$

$$p(X_i) = \frac{R(X_i)}{\sum_{j \in K} R(X_j)} \tag{7}$$

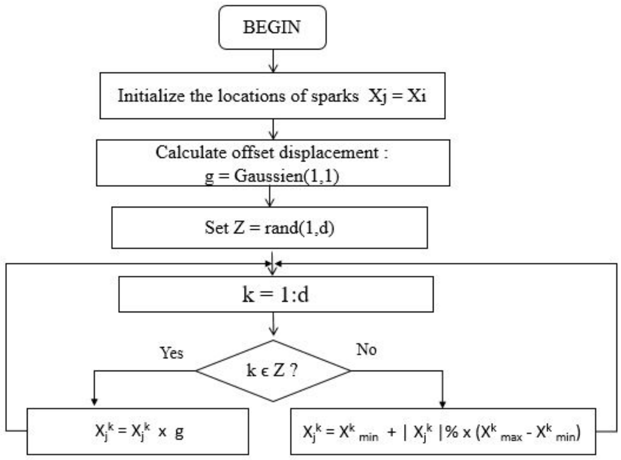

Fig. 5. Flowchart of mutation operator.

3. Fireworks Algorithm- Artificial Neural Network Method (FWA-ANN)

3.1. Design of the FWA-ANN Method

ANNs are described by the diagnostic efficiency of almost all photovoltaic faults [38-40]. ANN effectiveness refers to the value of weights and biases, which means, the right values of weights and biases are always manifested in the power of ANN. Although the ANN-based diagnostic model achieves good results, it cannot be denied that it is slowly converging in the training stage and the fault identification stage, the slow convergence of the ANN is caused by the limitation of the gradient process in the search for optimal weight and bias values leading to the weakness of this process in minimizing the error [30]. Hence the suggestion of a hybrid diagnostic method based on the Fireworks algorithm and artificial neural network (FWA-ANN) to optimize the ANN in terms of convergence and accuracy. The FWA-ANN model has combined the strength of the global search of the FWA algorithm with the local search of the ANN which offers rapid convergence by avoiding obtaining a locally optimal solution. Figure 6 shows the flowchart of the FWA-ANN model.

In the FWA-ANN method, the initial weights and biases of the neural network play the role of fireworks, before the learning phase, the weights and biases are optimized using the process steps of the FWA algorithm defined previously, Optimization is done by finding the optimal value of the fitness function, the mean squared error (MSE) is an objective function frequently used during neural network training because it has the advantage of severely penalizing values of error. The initial weights and biases optimized and obtained by the FWA algorithm are used to build and train the network, and they are optimized for the second time by again minimizing the objective function in the training phase to improve the performance of the diagnostic model and increase the efficiency of classification and identification of faults.

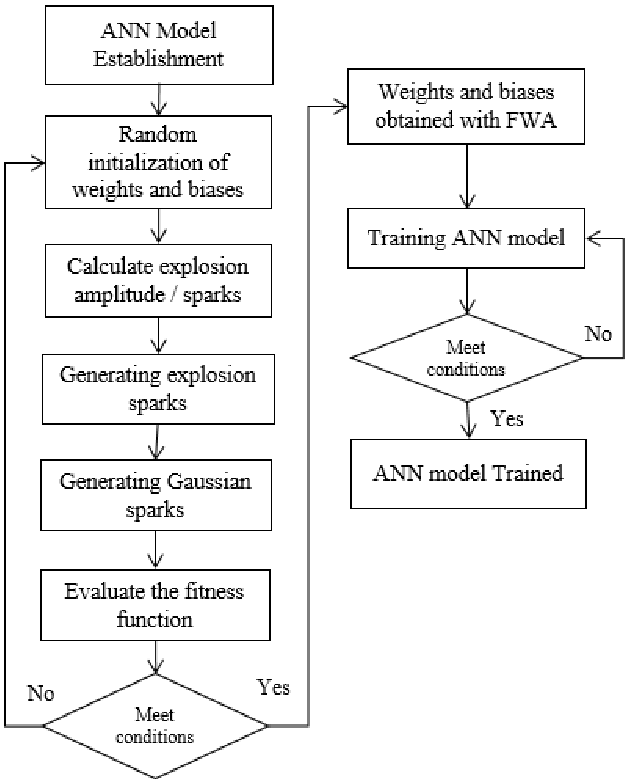

Fig. 6. Flowchart of the FWA-ANN method.

3.2. Configuring the FWA-ANN diagnostic model

The FWA-ANN model configuration in this study begins first with the collection of data necessary for training the model. The training data are the current Ipv and the voltage Vpv made up of 331315 samples. They are obtained by a photovoltaic field 4x4 (4 modules in series and 4 in parallel) under standard test conditions and various fault conditions, including partial shading fault, short circuit, and open circuit fault.

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 [41].

After we determine the structure of the neural network. It is an MLP network with three layers where the input layer contains 2 neurons, receiving the current Ipv and the voltage Vpv, the hidden layer has contained twelve neurons, and finally, the output layer was composed of four neurons, each neuron represents the state of the photovoltaic field, such as normal operation or one of type of fault (partial shading fault, short circuit fault, and open circuit fault). We also fitted the sigmoid tangent function as the activation function of the output layer to obtain the classification of the result as a probability.

Figure 7 shows a diagram of the FWA-ANN model used for the identification of faults in the photovoltaic field.

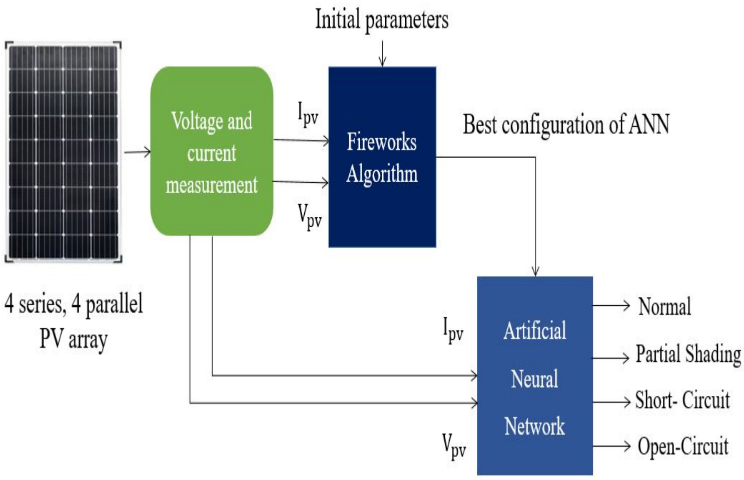

Fig.7. Schematic diagram of FWA-ANN model for diagnosing PV Field.

4. Results and Discussion

The combination of the FWA algorithm and neural network offers a fast and precise means in the diagnosis of failures of multiprocessor systems [42] and the diagnosis of concrete dams[43]. The objective of this study is the realization of a hybrid diagnostic model based on a neural network and the FWA algorithm to diagnose photovoltaic fields. We have chosen the current Ipv and the voltage Vpv delivered by the PV field to train the diagnostic model since these two parameters are given automatically by the field, which guarantees a fault diagnosis in real-time. The 331315 data collected are randomly divided into three groups, the first contains 70% of the data for the training step, 15% is used in the validation step while the remaining 15% is used for the testing step.

The FWA-ANN model was trained with the Levenberg-Marquardt (LM) algorithm as long as the diagnostic models based on neural networks and trained with the LM algorithm are achieved with good precision compared to the gradient descent [44-45]. Table 1 gives the main parameters of the FWA algorithm.

Table 1. Main parameters of the FWA algorithm

Parameters	Symbol	Value
Fireworks number	N	5
Max iteration	Tmax	100
amplitude coefficient	A	40
Sparks coefficient	M	50
maximum sparks number	Am	40
minimum sparks number	Bm	2
Upper bound	Xmax	0
Lower bound	Xmin	1

The fitness function adopted in the FWA-ANN diagnostic model is the Mean Square Error (MSE) given by equation (8). The adjustment of weights and biases of the neural network is done by minimizing the fitness function, a little value of the fitness function (close to zero), resulting in a very small value of the training error, and therefore better accuracy of the diagnostic model.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

The training error curves after the simulation of the FWA-ANN model and the ANN model are given in Fig.8 and Fig.9.

The formation of the ANN went through three main stages: the training stage, the validation stage, and the testing stage. Fig.7 and Fig.8 displays the error obtained during the three phases, including the error calculated in the training phase, the error calculated in the validation phase, and that calculated in the test phase, and the total training error is calculated from the error values obtained in each phase.

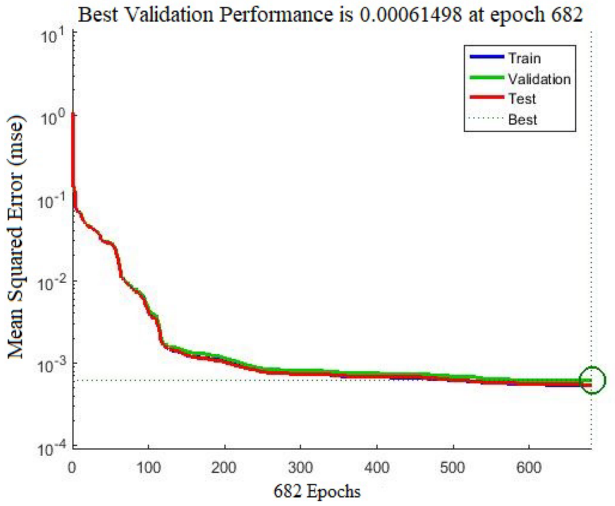

Fig. 8. Mean squared error of ANN model.

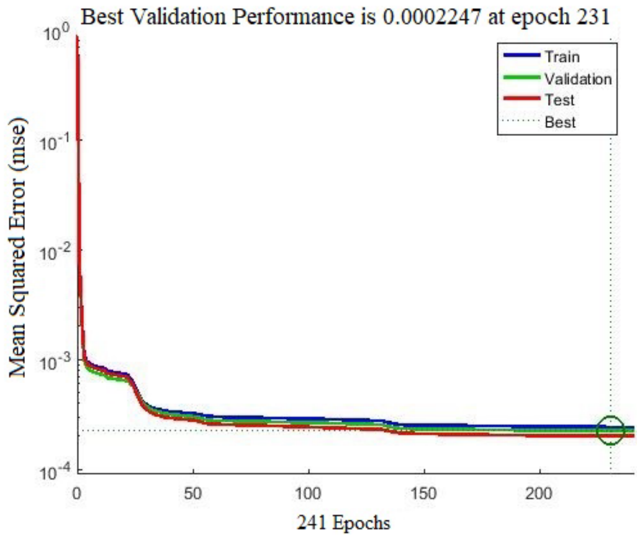

Fig. 9. Mean squared error of FWA-ANN model.

From the analysis of Fig.7 and Fig.8 of both experiments, we have proved that our method is more precise and faster. The calculation results have shown a large difference between the learning error of our proposed FWA-ANN model and the previous ANN model. In terms of numbers, the error measured during the validation step of the ANN model is equal to 6.1498e-4 while the average of the training error is equal to 5.5694e-4. The FWA-ANN model can reduce the average error of training to 2.338e -4, so that the hybrid model achieves 99.98% training accuracy, while the neural network-based model reached 99.94%.

Our novel hybrid FWA-ANN model reduced the learning time by less than a half compared to the previous ANN model, from 682 iterations to only 241 iterations. The promising impact of the FWA-ANN model on both the improvement of the classification accuracy and the acceleration of the convergence will contribute to future research advancement of the PV diagnostic systems based on the ANN model.

To verify the effectiveness of the FWA-ANN method, we performed a diagnostic model based on Particle Swarm Optimization (PSO) and the PSO-ANN neural network with the same parameters and the same ANN structure.

Particle Swarm Optimization (PSO) is a stochastic optimization metaheuristic proposed by Eberhart and Kennedy in 1995 [46]. It simulates the social behavior and movement of animals (insects, birds, and fish, etc.) in search of food. Table 2 summarizes the comparison between FWA-ANN and PSO-ANN.

According to the results cited in Table 2, it is remarkable that the FWA-ANN model outperforms PSO in terms of accuracy and convergence. Comparing the values of the fitness function obtained by each algorithm, we observed a big difference between the fitness function value obtained with the PSO algorithm which equals 6.8148, and that obtained with the FWA algorithm which equals 0.7793. The value of the fitness function plays an important role in reducing the learning error and the number of iterations, hence the reduction of the MSE error and the number of iterations in the FWA-ANN model. Compared to the PSO-ANN model, the FWA model has fewer error values and iterations, whereas PSO-ANN obtains an error equal to 4.9715e-4 in 564 epochs.

Table 2. Comparison between the FWA-ANN method and the PSO-ANN method

Model	PSO-ANN	FWA-ANN
Population Number	25	5
Iterations Number	564	241
Fitness function value	6,8148	0.7793
MSE	4,9715e-4	2,338e -4
Accuracy	99,95%	99,98%

In the reference [31], a hybrid method based on ANN and PSO algorithm is used to diagnose a PV system, the study in [47] has proposed to optimize the ANN with the genetic algorithm (GA) to identify PV faults. The analysis and comparison of results given in these studies and those given by our study, it cannot be denied that the PSO and GA algorithms were able to optimize the neural network, but compared to the FWA algorithm, the FWA remains more efficient and faster.

To verify the diagnostic model based on FWA-ANN, we have tested this model on a PV array under several states, which are composed of good functioning conditions, shading fault, short circuit fault, and open circuit fault. The results are shown in Table 3.

Table 3. Prediction accuracy of FWA-ANN and ANN model**.**

State of PV field	Scenarios	Predicted results	
		ANN	FWA-ANN
Partial Shading (PS)	Irradiation of the first column =800 W/m2	100%	100%
Normal (N)	Under standard test condition Irradiance = 1000 W/m2	100%	100%
Short-circuit (SC)	Two module are short-circuited	77.71%	99.56%
Open-circuit (OC)	Four modules are disconnected	87%	99.54%
Open-circuit (OC)	Six modules are disconnected	90%	99.7%
Short-circuit (SC)	Only one module is short-circuited	69%	98.52%
Partial Shading (PS)	Irradiation of the first line = 500 W/m2 & Irradiation of three modules in the first column = 500W/m2	97%	100%

From the experiments, it is clearly that the FWA-ANN-based diagnostic model has proved its importance in performance compared to the ANN model. However, the proposed system can be used for the diagnosis of different types of real-time PV systems satisfactorily.

4. Conclusion

The experiments that were performed to the extent of this work mainly focus on the accuracy elevating and the learning accelerating, we have implemented a PV field diagnostic system, based on a neural network optimized with the evolutionary FWA algorithm. The hybridization between ANN and FWA successfully–improved accuracy as well as minimizes convergence time. The simulation results proved that the FWA algorithm plays a crucial role in neural network optimization. The FWA-ANN increased accuracy up to 99.98%. For a concrete evaluation of our novel hybrid model, the FWA-ANN proposed in this work article was compared with the PSO-ANN model to verify its effectiveness. This comparison has reinforced our proposal that the FWA-ANN remains the best in neural network optimization.

The FWA-ANN diagnostic model is tested on a PV field, the results show that it is efficient to correctly classify the different states of the field, which demonstrates that this model is highly accurate.

In future studies, the diagnostic hybrid model will be used to identify other types of PV faults, moreover, a correction based on intelligent approaches of PV faults detected with the hybrid model will be studied in detail to facilitate the maintenance of PV installations.

Acknowledgements

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References

[1] ″ Stratégie Enérgetique Nationale Horizon 2030 ″, p.264, Ministére de l'Energie, des Mines de l'Eau et de l'Environnement, october 2019, Last accessed date : 11 March 2022.

[2] L. Bun, Détection et localisation de défauts dans un système photovoltaïque, p. 207.

[3] M. Hajji, M. Harakat F., A. Kouadri, K.Abodayeh, M. Mansouri, H. Nounou and M. Nounou, ″ Multivariate feature extraction based supervised machine learning for fault detection and diagnosis in photovoltaic systems ″, European Journal of Control, doi: 10.1016/j.ejcon.2020.03.004, April 2020.

[4] A. Appiah Y., X. Zhang, B. Ayawli B. K., and F. Kyeremeh, ″Review and Performance Evaluation of Photovoltaic Array Fault Detection and Diagnosis Techniques ″, International Journal of Photoenergy, doi: 10.1155/2019/6953530, vol. 2019, p. e6953530.

[5] S. Spataru, D. Sera, T. Kerekes, and R. Teodorescu, ″Diagnostic method for photovoltaic systems based on

light I–V measurements", Solar Energy, doi: 10.1016/j.solener.2015.06.020, vol. 119, p. 29-44.

[6] A. Mellit, G. Tina M., and S. Kalogirou A., " Fault detection and diagnosis methods for photovoltaic systems: A review ", Renewable and Sustainable Energy Reviews, doi: 10.1016/j.rser.2018.03.062, vol. 91, p. 1-17.

[7] S. Moulahoum, M. Hallouz, N. Kabache, and S. Kouadria, " Neural Network Based Field Oriented Control for Doubly-Fed Induction Generator ", International Journal of Smart Grid - ijSmartGrid, vol. 2, No:3.

[8] I. Yaichi, A. Harrouz, I. Boussaid, A. Semmah, P. Wira, I. Colak and K. Kayisli, " An Improved DTC Strategy for a DFIG using an Artificial Neural Network Controller », 9th International Conference on Smart Grid (icSmartGrid)", Setubal · Portugal, June 2021.

[9] M. Rana, I. Koprinska, and V. Agelidis G., "Forecasting solar power generated by grid connected PV systems using ensembles of neural networks ", International Joint Conference on Neural Networks (IJCNN), July 2015.

[10] R. Monteiro V. A., G. Guimarães C., F. Moura A. M., M. Albertini R. M. C., and M. Albertini K., " Estimating photovoltaic power generation: Performance analysis of artificial neural networks, Support Vector Machine and Kalman filter ", Electric Power Systems Research, doi: 10.1016/j.epsr.2016.10.050, vol. 143, p. 643-656.

[11] K. Chiteka and C. Enweremadu C., « Prediction of global horizontal solar irradiance in Zimbabwe using artificial neural networks », Journal of Cleaner Production, doi: 10.1016/j.jclepro.2016.06.128, vol. 135, p. 701-711,

[12] A. Almadhor, «Performance prediction of distributed PV generation systems using Artificial Neural Networks (ANN) and Mesh Networks ", International Conference on Smart Grid (icSmartGrid), Setubal · Portugal, December 2021

[13] W. Lin M., C. Hong M. and C. Chen H., "Neural-Network-Based MPPT Control of a Stand-Alone Hybrid Power Generation System ", IEEE Transactions on Power Electronics, doi: 10.1109/TPEL.2011.2161775, vol. 26, No 12, p. 3571-3581.

[14] S. Messalti, A. Harrag G., and A. Loukriz E., "A new neural networks MPPT controller for PV systems ", IREC2015 the Sixth International Renewable Energy Congress, March 2015.

[15] R. Ramaprabha, B. Mathur L., and M. Sharanya," Solar array modeling and simulation of MPPT using neural network ", Communication and Energy Conservation, International Conference on Control, Automation, June 2009.

[16] M. Karakose, M. Baygin, and K. Parlak S., «A new real-time reconfiguration approach based on neural network in partial shading for PV arrays ", International Conference on Renewable Energy Research and Application (ICRERA), Istanbul/Turkey October 2014.

[17] H. Mekki, A. Mellit, and H. Salhi, " Artificial neural network-based modelling and fault detection of partial shaded photovoltaic modules ", Simulation Modelling Practice and Theory, doi: 10.1016/j.simpat.2016.05.005, vol. 67, p. 1-13.

[18] W. Chine, A. Mellit, V. Lughi, A. Malek, G. Sulligoi, and A. Massi Pavan, "A novel fault diagnosis technique for photovoltaic systems based on artificial neural networks ", Renewable Energy, doi: 10.1016/j.renene.2016.01.036, vol. 90, p. 501-512.

[19] L. Jiang L. and D. Maskell L., " Automatic fault detection and diagnosis for photovoltaic systems using combined artificial neural network and analytical based methods ", International Joint Conference on Neural Networks (IJCNN), Killarney, Ireland, p. 1-8, July 2015.

[20] Syafaruddin, E. Karatepe, and T. Hiyama, " Controlling of artificial neural network for fault diagnosis of photovoltaic array ", 16th International Conference on Intelligent System Applications to Power Systems, Hersonissos, Greece, p. 1-6 , September 2011.

[21] S. Tchoketch Kebir, N. Cheggaga, A. Ilinca, and S. Boulouma, " An Efficient Neural Network-Based Method for Diagnosing Faults of PV Array ", Sustainability, doi: 10.3390/su13116194, vol. 13, No 11, p. 6194.

[22] Z. Li, Y. Wang, D. Zhou, and C. Wu, " An Intelligent Method for Fault Diagnosis in Photovoltaic Array ", System Simulation and Scientific Computing, Berlin, Heidelberg, p. 10-16, 2012.

[23] S. Zaki A., H. Zhu and J. Yao " Fault detection and diagnosis of photovoltaic system using fuzzy logic control ", 4th International Conference on Sustainable and Renewable Energy Engineering (ICSREE 2019), Beijing, China , July 2019.

[24] Y. Wu, Q. Lan and Y. Sun, "Application of BP neural network fault diagnosis in solar photovoltaic system ", International Conference on Mechatronics and Automation, Changchun, China, p. 2581-2585, August 2009.

[25] I. Karmacharya M. and R. Gokaraju, "Fault Location in Ungrounded Photovoltaic System Using Wavelets and ANN", IEEE Trans. Power Delivery, doi: 10.1109/TPWRD.2017.2721903, vol. 33, No 2, p. 549-559.

[26] W. Yin, Q. Tong, Y. Xu, Y. Zhang and Y. Zhou, " Partial Shading Impact on PV Array System and the Hard-Shading Location with BP Algorithm ", 7th International Conference on Smart Grid (icSmartGrid), Setubal · Portugal , December 2019.

[27] K. Pahwa, M. Sharma, M. Saggu S. and A. Kumar M., “Performance Evaluation of Machine Learning Techniques for Fault Detection and Classification in PV Array Systems ”, 7th International Conference on Signal Processing and Integrated Networks (SPIN), p. 791-796, February 2020.

[28] K. Wang, S. Li, and H. Zhang, “Application Research of BP Neural Network Optimization Based on Firefly Algorithm ”, J. Phys.: Conf. Ser., doi: 10.1088/1742-6596/1802/3/032040, vol. 1802, no 3, p. 032040, March 2021,

[29] Z. Liao, D. Wang, L. Tang, J. Ren and Z. Liu, “A Heuristic Diagnostic Method for a PV System: Triple-Layered Particle Swarm Optimization–Back-Propagation Neural Network”, Energies, doi: 10.3390/en10020226, vol. 10, no 2, p. 226,

[30] M. Colak, M. Yesilbudak and R. Bayindir, “ Daily Photovoltaic Power Prediction Enhanced by Hybrid GWO-MLP, ALO-MLP and WOA-MLP Models Using Meteorological Information ”, International Journal of Renewable Energy Research (IJRER), doi: 10.3390/en13040901, vol. 13, No 4, p. 901.

[31] M. Mishra and M. Srivastava, “A view of Artificial Neural Network”, International Conference on Advances in Engineering & Technology Research (ICAETR - 2014), Unnao, India, p. 1-3, August 2014.

[32] Y. Tan, Fireworks Algorithm (FWA) for Optimization, p. 93.

[33] X. Li G., S. Han F. and C. Gong Q., “Analysis and Improvement of Fireworks Algorithm”, Algorithms, doi: 10.3390/a10010026, vol. 10, No 1, p. 26.

[34] Y. Tan, Fireworks Algorithm. Berlin, Heidelberg: Springer Berlin Heidelberg, doi: 10.1007/978-3-662-46353-6, 2015.

[35] S. Zheng, A. Janecek and Y. Tan, Enhanced Fireworks Algorithm, p. 9.

[36] B. Li, C. Delpha, D. Diallo and A. Migan-Dubois, « Application of Artificial Neural Networks to photovoltaic fault detection and diagnosis: A review », Renewable and Sustainable Energy Reviews, doi: 10.1016/j.rser.2020.110512, vol. 138, p. 110512.

[37] E. Rojas-Martinez R., F. Macho-Hernantes, K. Stansfield E. and J. Colmenares-Quintero C., “Methodology for automatic fault detection in photovoltaic arrays from artificial neural networks”, Cogent Engineering, doi: 10.1080/23311916.2021.1981520, Vol 8, 2021.

[38] B. Basnet, H. Chun and J. Bang, “An Intelligent Fault Detection Model for Fault Detection in Photovoltaic Systems”, Journal of Sensors, doi: 10.1155/2020/6960328, vol. 2020, p. e6960328.

[39] S. Zaki, H. Zhu, M. Alfakih, A. Sayed R. and J. Yao, «Deep-learning–based method for faults classification of PV system ", IET Renewable Power Generation, doi: 10.1049/rpg2.12016, vol. 15.

[40] W. Gui, Q. Lu, and M. Su, “A Firewoks Algorithm-Back Propagation Fault Diagnosis Algorithm for System-level Fault Diagnosis “, JEIT, doi: 10.11999/JEIT190484, vol. 42, No 5, p. 1102-1109.

[41] S. Dou, J. Li, and F. Kang, "Health diagnosis of concrete dams using hybrid FWA with RBF-based surrogate model ", Water Science and Engineering, doi: 10.1016/j.wse.2019.09.002, vol. 12, No 3, p. 188-195.

[42] B. Laarabi, O. May Tzuc, D. Dahlioui, A. Bassam, M. Flota-Bañuelos and A. Barhdadi, “Artificial neural network modeling and sensitivity analysis for soiling effects on photovoltaic panels in Morocco ", Superlattices and Microstructures, doi: 10.1016/j.spmi.2017.12.037, vol. 127, p. 139-150.

[43] N. Sabri, A. Tlemcani and A. chouder, “Faults diagnosis in Stand-Alone photovoltaic system using Artificial Neural Network ”, 6th International Conference on Control Engineering & Information Technology (CEIT), Istanbul, Turkey, p. 1-6, October 2018.

[44] J. Kennedy and R. Eberhart, “Particle Swarm Optimization”, p. 7, 1995.

[45] A. Mohamed H., and A. Nassar , “New Algorithm for Fault Diagnosis of Photovoltaic Energy Systems”, International Journal of Computer Applications, doi:10.5120/20008-1959.