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Optimising Solar Power Plant Reliability Using Neural Networks for Fault Detection and Diagnosis

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***Abstract*—This study introduces an intelligent method to monitor grid-connected solar power stations, focussing on detecting problems in their energy output through the use of artificial neural networks (ANN). The main goal is to improve energy efficiency and bolster the reliability of solar power plants by forecasting their performance through real-time data analysis and modelling essential operational variables. The research was carried out in a solar field in AOULEF-ADRAR (South of Algeria), which covers six hectares and consists of 20,460 solar panels with an efficiency of 15 % to 20 %. The cumulative installed capacity is 5 MW, and the system is connected to a 30 kV electrical grid. The experimental findings validated the efficacy of the suggested ANN-based fault detection method. Subsequent to a sandstorm, the system exceeded standard operational limits, culminating in a total power overshoot of 200 KW. This procedure facilitated the identification of system faults and the execution of corrective measures, including the cleaning of PV modules to restore efficiency. The research highlights the importance of artificial intelligence (AI)-based monitoring systems to reduce downtime and maintenance expenses and guarantee consistent operation of photovoltaic plants under various environmental conditions. Research advocates for the integration of artificial neural networks with other machine learning methodologies, such as support vector machines, to improve fault prediction precision. Augmenting the data set by integrating data from various PV stations in different regions may improve the adaptability of the model to different environmental conditions. This method improves the creation of intelligent self-diagnosing solar power systems, promoting increased reliability and efficiency in the integration of global renewable energy.**

***Index Terms*—Synthetic neural network; PV system; Error detection; Diagnostic system; Residue analysis.**

I. INTRODUCTION

Renewable energy is a crucial component of global development strategies, with solar energy playing a significant role. Photovoltaic power stations, known as solar energy fields, are widely used to provide electricity to the grids as demand. This technology is gaining popularity due to its sustainable production methods [1], [2]. Solar energy effectively helps reduce greenhouse gas emissions and dependence on fossil fuels, improve environmental quality, and reduce energy costs. Solar power stations are crucial to achieving sustainable development objectives and environmental sustainability [3]–[5].

The increasing use of solar energy reflects the global commitment to transition to renewables, achieve energy independence, and stimulate sustainable economies and job creation. Investing in solar energy infrastructure and research and development can significantly contribute to goals of global economic and environmental development [6], [7]. Despite the advantages of photovoltaic systems, they come with certain drawbacks.

These include susceptibility to weather-related problems such as clouds and rain, along with high maintenance costs. Furthermore, their operation is dependent on sunlight availability [8]–[11], rendering them inactive at night and on cloudy days, which requires extensive energy storage solutions. Consequently, researchers are actively exploring effective fault detection methods for photovoltaic power stations. Numerous scientific studies are dedicated to improving system reliability and developing novel techniques for fault monitoring and diagnosis, all of which aim to improve maintenance efficiency and the overall performance of these crucial systems.

Artificial intelligence (AI) approaches, particularly neural networks, are used to control and diagnose photovoltaic installations in extremely hot places where summer temperatures can exceed 50 °C. They evaluate performance information, keep an eye on weather and sun radiation, and forecast problems [12]–[14].

To increase the performance of solar stations in hot conditions, neural networks build data-driven models and provide precise operational and maintenance assistance for fluctuating weather conditions.

In this study, artificial neural networks were used to

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detect faults in a photovoltaic power station located in the high temperature Aoulef-Adrar region of southern Algeria. These networks effectively diagnosed faults, even in the presence of capacity and noise errors.

This approach offers a streamlined method for fault detection, avoiding the need for complex mathematical models and utilising measurements from the photovoltaic system. It aims to identify hard-to-detect faults in photovoltaic systems, particularly in challenging weather conditions, which can reduce station efficiency. Modern monitoring strategies are crucial to maintaining consistent performance and predicting future outcomes in such variable environments.

II. THE PHOTOVOLTAIC POWER PLANT IN AOULEF, LOCATED IN SOUTHERN ALGERIA

Due to its advantageous geographic location, Algeria boasts one of the world's largest solar fields. Across the nation, the average annual solar exposure is nearly 2,000 hours, reaching as high as 3,900 hours in elevated and desert areas. Solar energy reception ranges from 1.5 kilowatt hours (kW) per square metre in northern regions (approximately 1,860 kW annually) to 6.6 kWh in the expansive southern areas (approximately 2,410 kW yearly). The solar power station is notable located in the "AOULEF" region in southeast of Adrar province. This facility officially opened on 6 March 2016 with a production capacity of (5 MW) over a 10-hectare area, as shown in Fig. 1.

Fig. 1. A segment of the Aoulef photovoltaic power station situated in southern Algeria.

The AOULEF photovoltaic power station, located in the Sahara Desert, comprises five solar fields with a total capacity of 5 MW. Equipped with a dedicated weather station, it monitors key environmental parameters such as solar irradiation (exceeding 1,200 W/m²), temperature, humidity, atmospheric pressure, and wind speed and direction. These data improve performance optimisation and forecasting. Despite the challenges posed by extreme desert conditions, such as high temperatures, sand accumulation, and wind storms, the station demonstrates the resilience of advanced photovoltaic technology. AOULEF exemplifies Algeria's strategic use of its abundant solar resources to promote clean energy and national energy independence. Expanding such projects promises environmental and economic benefits for the region.

III. PROPOSED METHODOLOGY

The main objective of the proposed methodology is to identify problems in the underresearched photovoltaic system using a diagnostic approach utilising ANN, consisting of three fundamental stages (Fig. 2).

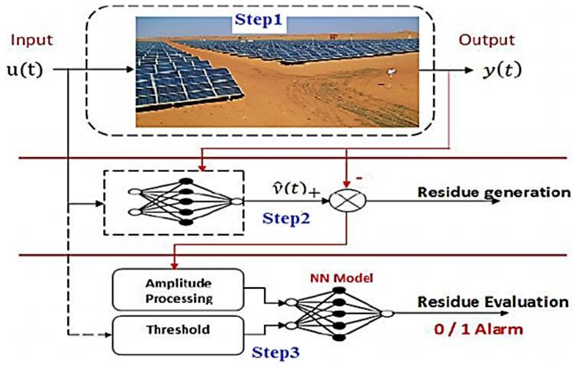

Fig. 2. The suggested strategy employing the neural network methodology.

During the initial step, actual outputs of the system are generated, representing the power produced by the actual photovoltaic system.

In terms of the second step, residues are created from the comparison of actual output (power produced by the system) with the neural network model. Finally, in the third step, the residues that indicate a difference between the real system and the trained neural network model are input into another neural system trained with a predefined threshold for evaluation.

The final result is represented with "0" to signify No defect, i.e., the power of the system is greater than the threshold, or "1" as an indication of a malfunction, the power of the system is below the threshold (residual and threshold). And in case a defect is detected, a warning signal is issued in the form of sound or light. The relationship between residues and outputs is as follows

$$r(k) = \hat{Y}(k) - Ym(k). \tag{1}$$

Ym (k) denotes the output of the observed system, while $\hat{Y}(k)$ signifies the expected or predicted output of the system. As part of the diagnostic process for the system in question, the power (*P*) residuals are analysed.

The diagnostic method involves evaluating the neural network model, which is expressed as

$$P = RNN(G,T). \tag{2}$$

IV. MODELLING OF SOLAR CELLS

The primary goal of photovoltaic cell modelling is to characterise the relationship between voltage and current produced by a solar panel under various operating conditions. Extensive empirical research over the past few decades has led to the formulation of mathematical models that can simulate the electrical performance of photovoltaic systems.

The most prevalent analytical models are the single-diode and double-diode models (Fig. 3), which represent the photovoltaic cell through an equivalent electric circuit containing one or two diodes.

These models provide critical predictive capabilities for forecasting the impact of environmental parameters such as solar irradiation intensity, ambient temperature, and incident light spectrum on the power output capabilities of photovoltaic cells. Accurate modelling and computer simulations enable system designers to optimise overall system efficiency and evaluate performance trade-offs for different photovoltaic technologies and applications. Additionally, they assist researchers in identifying limitations and degradation mechanisms in existing designs.

The fundamental physics governing carrier generation transport and recombination processes within the cell must be thoroughly understood to produce realistic simulations. The continued advancement of photovoltaic analytical models, validated through experiment, promises to facilitate cost-effective solar cell design and testing capabilities [15], [16].

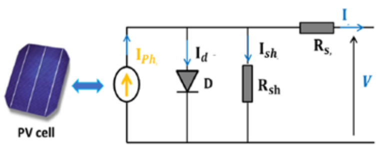

Fig. 3. Single-diode photovoltaic cell model.

The expression of this model takes the form of an implicit equation, and numerous researchers have discussed this equation in their publications [17]

$$I = I_{ph} - I_0\left(e^{\frac{q(v+R_sI)}{akTNs}} - 1\right) - \frac{V+R_sI}{R_{sh}}, \tag{3}$$

where I_{ph} stands as photocurrent, I_0 represents the reverse saturation current, R_{sh} is the shunt resistance, R_s is the series resistance, and V represents the thermal voltage; I is the module current and a is the ideality factor

$$I_{ph} = \left(I_{sTc} + k_i\left(T - T_{sTc}\right)\right)\frac{G}{G_{STC}}, \tag{4}$$

where T is the location temperature, I_{stc}, T_{sTc}, and G_{sTc} are the solar intensity (photocurrent), temperature, and irradiance at the Standard Test Conditions for the solar panel. The diode's reverse saturation current can be expressed as described in the references [18]–[20]

$$I_0 = \frac{I_{sTc} + k_i\left(T - T_{sTc}\right)}{e^{\left(\frac{q\left(V_{OC} + k_p\left(T - T_{sTc}\right)\right)}{akTN_s}\right)} - 1}, \tag{5}$$

where q represents the electronic charge (q = 1.60218 × 10−19 C), k represents the Boltzmann constant (K =1.38006 * 10−23 J/K), and Tc is the cell temperature. The photovoltaic panel used in the Adrar solar power station exhibits specific characteristics, as outlined in Table I.

This solar module is equipped with a solar spectre with an irradiance of 1000 W/m^2 and maintains a cell temperature of 25 C °. These distinctive features play a crucial role in enhancing the efficiency and overall performance of the photovoltaic system at the Adrar solar power station.

Optimising irradiance and cell temperature is crucial to maximise solar panel efficiency. Real-time measurements of power, temperature, radiation, and humidity were collected at the Aoulef-Adrar solar plant. The purpose of the process is to conduct analyses of the specific parameters for the photovoltaic power station that has been examined, taking into account temperature and radiation variations.

These measurements were carried out continuously over a three-day period, spanning from 6:00 am to 8:00 pm, during the month of July. The recorded humidity levels fluctuated between 5 % and 25.2 % (Fig. 4), with solar radiation measurements ranging from 0 to 1079.1 W/m2 (Fig. 5). The temperature readings ranged from 32.2 °C to 48.9 °C (Fig. 6), and the total power production of the station ranged from 0 kilowatts to 3131 KW (Fig. 7).

TABLE I. ELECTRICAL PROPERTIES OF A SOLAR PANEL.

Maximum power	245 W (0/+5 W)
MPP Voltage (Vmp)	29.6 V
MPP Current (Imp)	8.28 A
Max series fuse	15 A
Open circuit voltage (Voc)	37.5 V
Short circuit current (Isc)	8.83 A

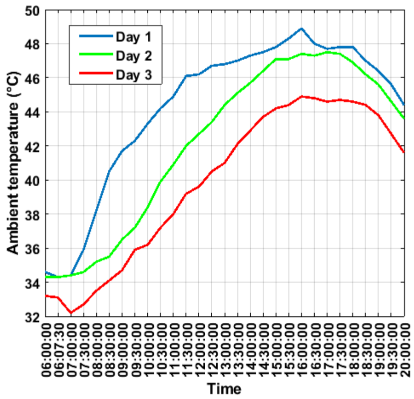

Fig. 4. Ambient temperature in the solar power station studied.

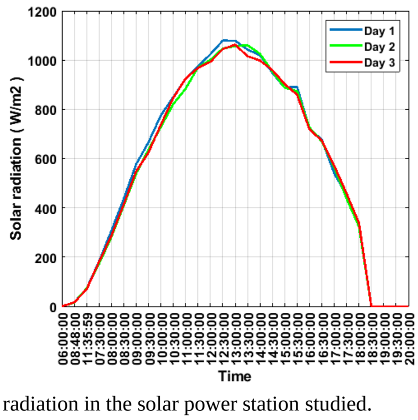

Fig. 5. Solar radiation in the solar power station studied.

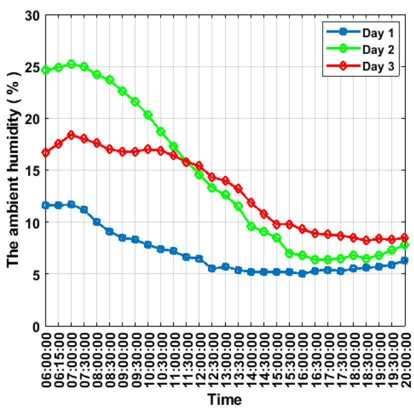

Fig. 6. Ambient humidity in the solar power station studied.

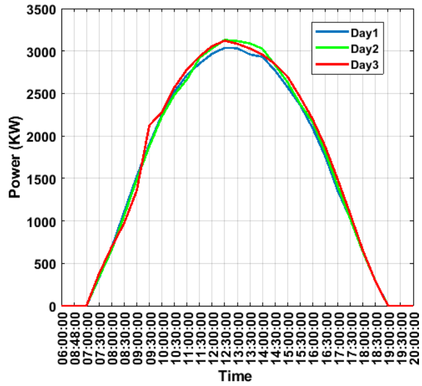

Fig. 7. Power generated in the solar power station studied.

V. DIAGNOSTIC OF PHOTOVOLTAIC SYSTEMS BASED ON NEURAL NETWORKS

Artificial neural networks mimic the human brain's ability to process information, recognise patterns, and adapt. They are widely used in AI and machine learning for tasks such as computer vision, speech processing, data analytics, and process modelling.

ANNs continuously refine their predictions, making them highly adaptable in dynamic environments. Their ability to learn and improve over time enhances decision making and pattern recognition, driving innovation in various industries [21], [22]. The neural network model developed to characterise the solar photovoltaic system follows multilayer feed forward architecture, as depicted in Fig. 8. This model consists of one hidden layer with 10 neurons and an output layer. The input layer accepts key independent variables, namely ambient temperature and incident solar irradiation on photovoltaic panels, which influence power generation. The output layer predicts the net energy yield from the photovoltaic plant. The network is trained, validated, and tested using historical operational data from the actual solar facility under study. Of the total data, 70 % is used for training, allowing the network to learn the relationships between input parameters and output power. Additionally, 15 % of the data is reserved for cross-validation during training to fine-tune the hyperparameters and prevent overfitting. Finally, the trained network, with its optimised topology, is tested on the remaining 15 % of unseen data to assess its generalisation capability in predicting energy output under previously unknown conditions. Using real empirical data enables the neural model to accurately capture complex nonlinear patterns, ensuring reliable performance and predictions.

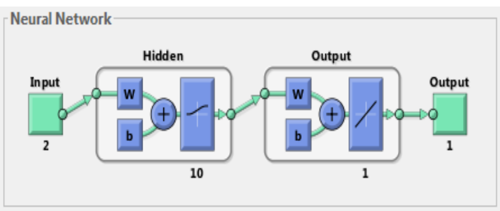

Fig. 8. Proposed artificial neural networks.

The hidden layer comprises an interconnected web of processing units with nonlinear activation functions that identify and store the intricate relationships between inputs and outputs. Through supervised learning of the training data, the network continuously tweaks its internal parameters until the model can accurately forecast photovoltaic power generation under various operating conditions. The validated neural network promises to support smarter control and management of the solar plant in the case study [20], [23]. To improve performance and accuracy, this neural network uses a learning rule and backpropagation to adjust its internal parameters and iteratively weights, minimising the squared error defined by (6); this iterative learning process improves the ability of the network to make precise predictions in solar system diagnostics [1], [24], [25]

$$E = \frac{1}{2}\sum_i (d_i - y_i)^2 = \frac{1}{2}\sum_i \left(d_i \sum W_{ij} x_j\right)^2. \tag{6}$$

The change in weight, denoted as W_{ij}, when modified by an amount ΔW_{ij}, should be directly proportional to the error gradient as follows [1], [26], [27]

$$\Delta W_{ij} = -\eta \frac{dE}{dW_{ij}} = \eta \sum_i (d_i - y_i) x_i. \tag{7}$$

The activation function calculates the neuron state value using this value before transmitting it to neurons downstream [1], [26]

$$y_i = \varnothing(a_i - \theta_i). \tag{8}$$

Both the hidden layer and the output layer generate the following outputs:

$$U_i = f_1 \sum_{i=1} W_{ij}^1 x_i + W_{ki}^1 x_k + b_j^1, \tag{9}$$

$$y_k = f_2 \sum_{i=2}^{N} \left(u_1 + b_k^2\right), \tag{10}$$

where x_i is the input of the neuron, w_{ij} is the synaptic weight value of the connection that goes from neuron j to neuron i. The relationship between the sigmoid activation function f_1 and the linear activation function f_2 is expressed as follows

$$\begin{bmatrix} f_1(v) = \dfrac{2}{1+e^{-2v}} - 1, \\ f_2(v) = v. \end{bmatrix} \tag{11}$$

Method served as the foundation for E, which is described below [27]–[29] is used to reduce the cost function gradient

$$E_p(W) = \frac{1}{2}\sum_{i=1}^{m}\left[y_i^d(k) - \hat{y}_i(k)\right]^2. \tag{12}$$

VI. DISCUSSION AND RESULTS

The purpose of this study is to use actual measurement data to model the behaviour of the PV facility at AOULEF. An intelligent model based on ANN is created to identify and pinpoint system flaws. The principal aim is to assess the effectiveness of the intelligent model in detecting flaws under different weather conditions after comparing it with the reference model under healthy operating settings.

Average power production over three days is shown in Fig. 9, while Fig. 10 presents the root mean square error, which is on the order of 10^{-3}.

This study uses an artificial neural network model that takes solar irradiance and ambient temperature as input variables to predict power output. The data preprocessing pipeline incorporates two normalisation techniques: initial scaling of the feature to a uniform distribution followed by Min-Max normalisation, which transforms both the input and output variables into the range [-1, 1].

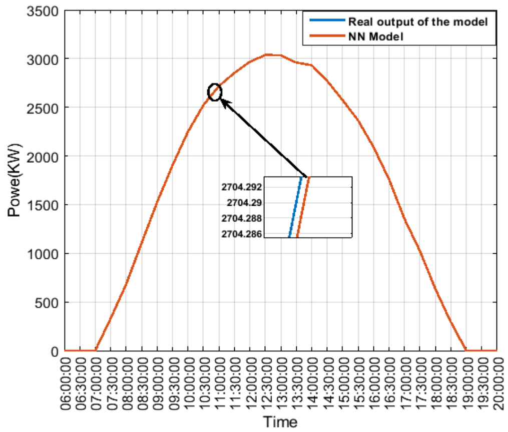

Fig. 9. Output model ANN and real model.

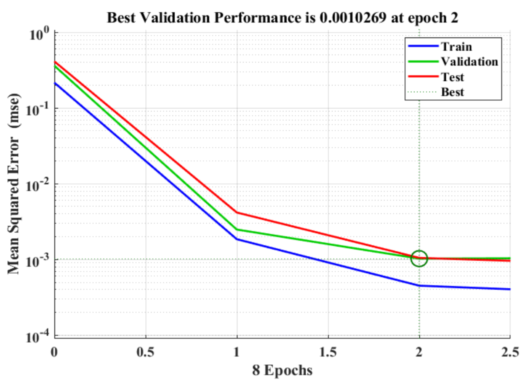

Fig. 10. NN performance model.

To further evaluate the robustness of the proposed model, statistical coefficient analysis was performed, with the results presented in Fig. 11.

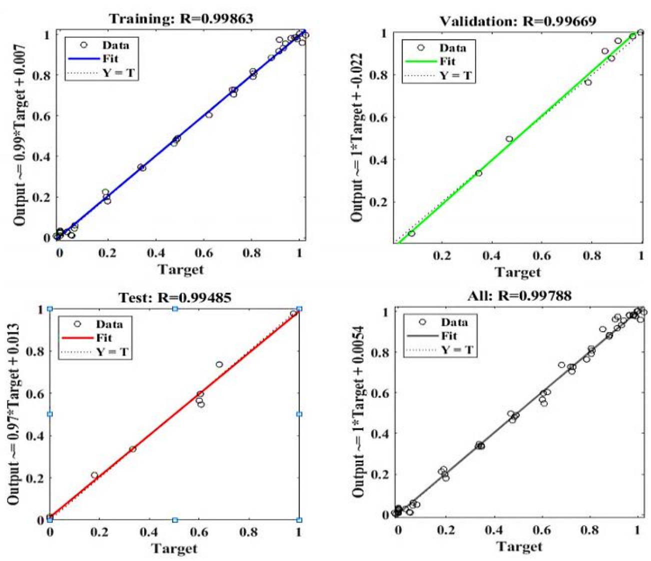

Fig. 11. Correlation of the neural model.

The backpropagation algorithm, depicted in Fig. 12, is employed to minimise errors during training, enabling the network to learn complex input-output relationships. A structured data aggregation pipeline integrates diverse weather variables and energy output measurements into a consistent format, facilitating the application of the proposed machine learning technique. Rigorous preprocessing and normalisation ensure effective model development, allowing for accurate and generalisable photovoltaic power predictions under unseen conditions. Additionally, an automated diagnostic system based on artificial neural networks is implemented to detect faults in the PV system.

Through extensive parametric studies, including network type selection and input-output optimisation, the model is validated for identifying mismatch faults caused by varying illumination intensities and sudden variations in temperature brought on by geographical and meteorological factors. The results confirm the effectiveness of neural networks in automating fault diagnosis, with the model learning from a reference state until achieving the selected mean square error (MSE), enabling real-time defect detection between reference and neural models.

To compare the actual power values of P_{real} and the predicted values of the neural network P_{ANN}, several analytical and statistical methods can be used, such as:

– Mean Absolute Error (MAE)

Measures the average absolute difference between actual and predicted values and is given by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_{real,i} - P_{ANN,i}\right|. \tag{13}$$

The computed value is 4.99×10^{-3}.

– Mean Absolute Percentage Error (MAPE)

Expresses the error as a percentage of actual values and is calculated as

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{P_{real,i} - P_{ANN,i}}{P_{real,i}}\right|. \tag{14}$$

Since the data set contains zero values, some ratios are undefined. However, when calculated for nonzero values, it is 1.67×10^{-4} %.

– Mean Square Error (MSE)

Quantifies the average squared differences between actual and predicted values and is defined as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(P_{real,i} - P_{ANN,i}\right)^2. \tag{15}$$

The computed value is 1.98×10^{-5}.

These results indicate the extremely high accuracy of the artificial neural network model in estimating the power output of the photovoltaic system.

Figure 13 compares the baseline power model with the defective model. It is evident that the model with defects produces less measured power than the healthy model anticipates. The study shows the measured power residuals between two models for the solar station in Fig. 14. System failures are identified using a 200-kW power threshold.

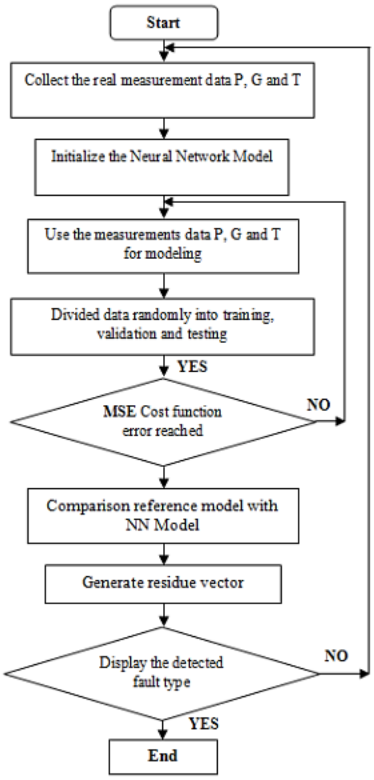

Fig. 12. NN modelling system flow chart.

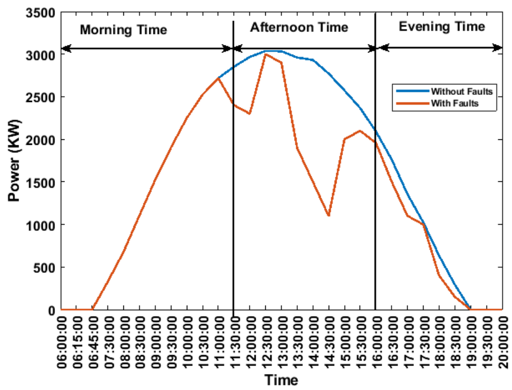

Fig. 13. Reference model and healthy for power.

The comparison of healthy system energy production with actual system condition, indicated by a change from “0” to “1” in the diagnostic system output, was significantly improved by the methodology. This change is blatant evidence of a system problem, primarily caused by a sharp drop in power output, as seen in Fig.15.

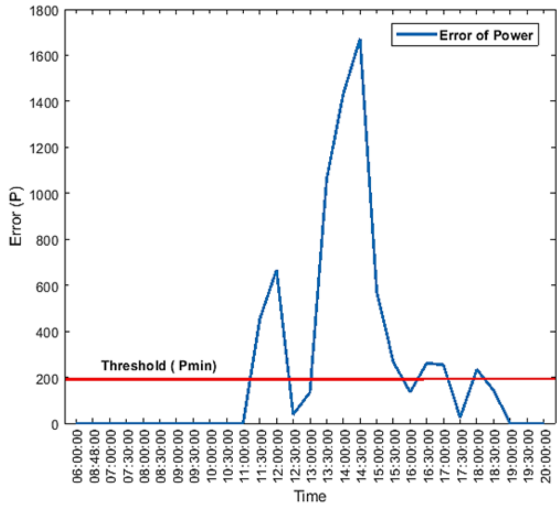

Fig. 14. Residual errors of the power model.

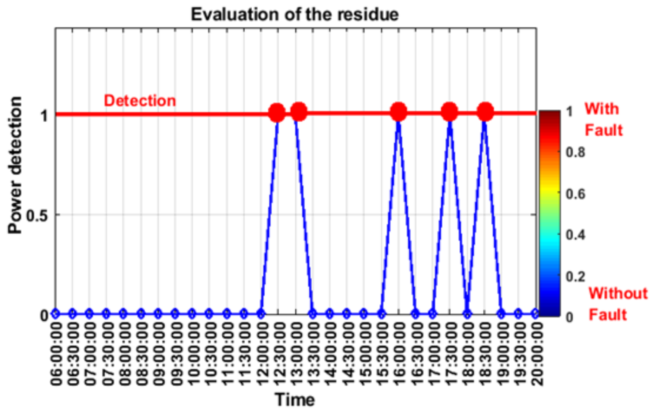

Fig. 15. Evaluation of the residues of the remaining power of the photovoltaic station connected to the grid under study.

This result highlights the ability of the methodology to efficiently identify system problems by carefully observing changes in power output and instantly sending out notifications when a significant decrease takes place.

TABLE II. COMPARISON OF THE PRESENT STUDY WITH PREVIOUS STUDIES.

Ref.	Year	Input/Output			ANN Technique	Result
		T	G	P		
[31]	2016	✓	✓	✓	MLP	The ANN-based method accurately detects and classifies PV faults, validated on FPGA with XSG and ISE
[32]	2019	✓	✓	✓	MLP	Efficient fault detection in PV arrays using FNN
[33]	2020	✓	✓	✓	MLP	SCG-based MNN classifies PV faults with 99.6 % accuracy in 0.08 s, improving efficiency and reliability
[34]	2021	✓	✓	--	MLP	PNN excels in PV fault diagnosis, while BPNN and GRNN offer high speed and accuracy.
[35]	2018	✓	✓	--	RBF	RBF-ANN and fuzzy logic detect PV faults with a 92.1 % accuracy
[36]	2020	--	✓	✓	RBF	RBF-ANN detects PV faults with 97.9 % accuracy, even in partial shading
[37]	2017	--	✓	✓	DANN	The ANN-based system estimates power and detects faults in PV modules, improving reliability and efficiency
[38]	2022	✓	✓	✓	MLP, PNN, RBF, CNN, SAE	The study reviews ANN models for PV fault diagnosis, focussing on performance and challenges
[39]	2020	✓	✓		NARX	Fuzzy NARX detects PV faults with high accuracy and IoT support
[40]	2020	✓	✓	--	CNN	The CNN-Res-GRU model achieves 98.61 % accuracy in PV fault the classification without temperature or irradiance data
Present study	**2025**	**✓**	**✓**	**✓**	**MLP**	**This study uses artificial neural networks for fault detection in solar stations, enhancing performance monitoring and alerting for power drops**

A comparison of the results of the present study with previous studies, as shown in Table II, reveals that AI-based techniques have made significant advancements in ANN methods for fault detection in PV systems. These techniques have continuously improved accuracy and response time. Meanwhile, the current study presents improvements in using MLP for fault detection in solar power stations, which contributes to better monitoring and reduced system downtime.

VII. CONCLUSIONS

This study introduces a novel approach using artificial neural networks to improve monitoring and fault detection systems at a grid-connected solar power station located in AOULEF, Southern Algeria. This research focusses primarily on the management of climatic variations, including temperature and solar radiation fluctuations. The results, compared to earlier studies, strongly support the effectiveness of this method in identifying problems through system operation analysis. This method enables prompt and effective decision making that enhances station performance and minimises unexpected downtime.

The proposed methodology forecasts the behaviour of the system using actual fault data collected on site. The ANN-based diagnostic method uses field-acquired input/output measurements. We initially identified operational models for the photovoltaic system leveraging MLP neural network techniques. In the following phase, the actual station measurements were juxtaposed with the predicted values to evaluate the accuracy of the model. The findings exhibited exceptional accuracy in identifying and predicting energy reduction faults, markedly improving the reliability of the system.

Comparative analysis between ANN-based models and those that represent actual system behaviours highlights the significant advantages of this method for proactive maintenance and enhancing the environmental and economic performance of stations.

This research presents new avenues for future research, including:

– Examining the resilience of fault-tolerant control systems in grid-connected photovoltaic stations;

– Enhancing predictive maintenance methodologies through AI techniques to minimise operational expenses and extend system longevity;

– We are enhancing diagnostic techniques to identify multiple concurrent faults in grid-connected photovoltaic systems.

This study underscores the significance of AI methodologies, such as neural networks, in improving the efficiency of solar energy systems, advancing the sustainability of renewable energy and facilitating the global development of energy infrastructure.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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