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Diagnosis of a stand-alone photovoltaic installation by the Analytical Redundancy Relationship method (ARR)

***Abstract**. Solar energy is one of the most important renewable sources to replace fossil fuels for electric power generation. like other energy systems, it is susceptible to several faults and anomalies during operation, which can reduce its performance and productivity. This paper provides a diagnostic method based on the Analytical Redundancy Relation (ARR) method for detecting faults in off-grid photovoltaic systems. This method is based on the calculation of residues between the modules and the PV system, which enables more accurate faults detection and anomalies. Additionally, a comprehensive structure to diagnose the effect of rainfall on PV installations has been designed. The proposed approach is evaluated using a MATLAB/Simulink simulation model, and the results demonstrate the effectiveness of the ARR method in detecting faults in PV systems. The developed structure is also able to diagnose the impact of rainfall on the performance of PV installations. The results obtained can help improve the performance and reliability of PV systems, which can contribute to the wider adoption of solar energy as a clean and sustainable energy source.*

Streszczenie.** Energia słoneczna jest jednym z najważniejszych źródeł odnawialnych zastępujących paliwa kopalne w procesie wytwarzania energii elektrycznej. podobnie jak inne systemy energetyczne, jest on podatny na szereg usterek i anomalii podczas pracy, co może zmniejszyć jego wydajność i produktywność. W artykule przedstawiono metodę diagnostyczną opartą na metodzie analitycznej relacji redundancji (ARR) służącą do wykrywania uszkodzeń w systemach fotowoltaicznych poza siecią. Metoda ta opiera się na obliczeniu pozostałości pomiędzy modułami a systemem PV, co umożliwia dokładniejsze wykrywanie usterek i anomalii. Dodatkowo zaprojektowano kompleksową strukturę do diagnozowania wpływu opadów atmosferycznych na instalacje PV. Zaproponowane podejście zostało ocenione przy użyciu modelu symulacyjnego MATLAB/Simulink, a wyniki wykazały skuteczność metody ARR w wykrywaniu usterek w systemach fotowoltaicznych. Opracowana konstrukcja umożliwia także diagnozowanie wpływu opadów atmosferycznych na pracę instalacji PV. Uzyskane wyniki mogą pomóc w poprawie wydajności i niezawodności systemów fotowoltaicznych, co może przyczynić się do szerszego przyjęcia energii słonecznej jako czystego i zrównoważonego źródła energii.* (Diagnoza autonomicznej instalacji fotowoltaicznej metodą analitycznej zależności redundancji (ARR))***

Keywords: Diagnosis, Fault detection, ARR, Photovoltaic, Renewable energy.
Słowa kluczowe: Diagnostyka, wykrywanie usterek, ARR, fotowoltaika, energia odnawialna

Introduction

The increasing demand for energy in industrial and developing countries has led to the overuse of fossil fuels, leading to increased gas emissions and pollution. These emissions impact the environment, deplete natural resources and thereby became a threat to future generations. In order to mitigate these issues, renewable energy sources like solar and nuclear energy have been gaining popularity. Photovoltaic (PV) technology is one of the most widely used renewable energy owing to its ability to reduce pollution and preserve the environment. However, PV installations are prone to failure and deterioration over time which can reduce their effectiveness. For that, it requires accurate diagnostics to detect faults and determine their type. This can facilitate maintenance and reduce costs while increasing energy production.

Over the years, several diagnostic methods have been proposed in the literature, including those that compare real-time parameters with data predicted by the model or analyse the difference between the model's predicted power ratio and the real-time ratio. Theoretical parameters are calculated using a PV model, and these parameters are then compared to real-time parameters to identify the presence of defects in the system. To improve the management principles of a photovoltaic system with storage battery and with autonomous operation during daylight hours, an algorithm based on real-time measurements with different shading situations is used for monitoring PV modules [1]. Also, to optimize the performance of the PV system and improve energy production, an algorithm for maximum power point tracking (MPPT) based on real-time measurements with different shading situations for monitoring PV modules is proposed [2][3]. An automatic fault detection method for grid connected PV plants based on analysing the difference between the model's predicted power ratio and the real-time power ratio to detect the defect is proposed [4]. Furthermore, an approach based on comparing real-time system losses with model-predicted losses in order to detect shading defects and differentiate them from other defects in the system is proposed [5]. Also, a proposed study based on analysing the voltage-current characteristic of the PV panels for domestic applications, using a simulated PV panel model for detection and location of the different types of faults in the system [6].

The advancements in technology over the past few years have led researchers to explore newer and more sophisticated diagnostic methods to identify defects in PV systems. A neuro-fuzzy method for detecting faults in PV systems has been introduced [7][8][9]. This method involves training a model to recognize patterns and identify anomalies in the data. Then, a methodology for fault detection and diagnosis in the DC side of PV systems using a probabilistic neural network (PNN) classifier is presented [10][11]. This approach was evaluated on both noiseless and noisy data and highlights the potential of using PNN-based methods for improving the reliability and performance of PV systems. Also, a new approach for analysing module defects in large-scale PV farms using deep learning techniques is presented. This approach involves a deep learning-based solution to identify and classify different types of module defects using aerial images captured by drones [12]. Furthermore, Domain adaptation combined with deep convolutional generative adversarial network (DA-DCGAN) are proposed for DC series arc fault diagnosis in PV systems [13][14]. The proposed method generates dummy arcing data using normal data from the target domain and employs domain adaptation for fault diagnosis. Also, two enhanced Random Forest (RF) classifiers, RK-RFED and RK-RFKmeans, are proposed for fault detection and diagnosis (FDD) of industrial processes, and are validated using an emulated grid-connected PV system [15]. These classifiers are based on kernel principal component analysis and consist of two main stages that are feature extraction and selection, and fault classification. A nature-based algorithm that works on the principle of plant propagation to solve the problem of partial shading has been proposed [16][17]. This algorithm is designed to track the global peak under different shading conditions in order to extract the maximum possible power from the PV system. Recently, a combination of machine vision and lazy learning approach has been applied to for fault diagnosis of PV modules [18][19]. The proposed method extracts features from PV module images and applies a lazy learning algorithm to classify faults.

In this context, this paper aims to provide an integrated system for detecting defects [20] in off-grid photovoltaic systems using the Analytical Redundancy Relation (ARR) method. The goal is to provide users with monitoring and diagnostic services to facilitate maintenance and reduce costs while increasing energy production. This method is based on the residual calculation between the estimated module and the photovoltaic installation, which contradicts the calculation of the power in the PV installation. The model is developed using MATLAB/Simulink and includes a defect detection structure. It presents a new and scalable method for defect diagnosis of photovoltaic systems.

Different theoretical approaches to diagnosis

The detection and localization of faults in monitoring systems require obtaining characteristic symptoms of the monitored process operation and analyzing them to deduce the system's state. To establish these symptoms, it is necessary to have prior knowledge of healthy behavior. The shape of the symptoms, which can include noise, temperature, electrical quantities, and other factors, and the method used to generate them, depend on the type of knowledge available. Diagnostic methods can be classified based on the form of knowledge used and the resulting analytical method. Figure 1 presents an overview of the major diagnostic methods [21][22].

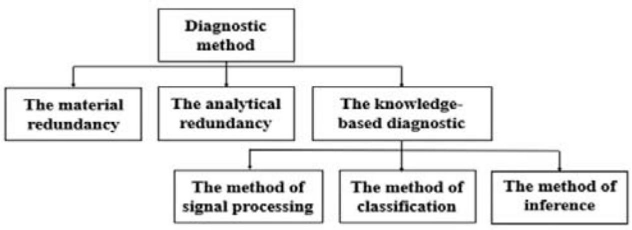

Fig. 1.Diagnostic methods

The material redundancy method

This method involves using multiple components, such as sensors, actuators, or generators, to perform the same function. By comparing the outputs of these components, any discrepancies can indicate the presence of a defective component. In the context of photovoltaics, this method is sometimes used in certain inverters to identify the weakest string. However, it is important to note that this method is limited in its ability to identify the nature of any defects that may be present.

The analytical redundancy method

The analytical redundancy method involves inferring the state of the monitored system or process based on measurements of its input and output quantities. This approach typically requires a state model that can accurately represent the system being monitored.

The material redundancy method

The knowledge-based diagnostic method can be broadly categorized into three main families: signal processing, classification, and inference. The signal processing method involves analyzing the signals from the monitored system to detect any abnormal patterns or deviations from normal behavior. The classification method involves comparing the signals from the monitored system with a library of known patterns to identify any similarities or differences. The inference method involves using a model of the system to make predictions about its behavior based on the available data. By employing one or more of these approaches, knowledge-based diagnostic methods can provide valuable insights into the health of a system and help to identify any faults or anomalies.

Generation and evaluation of residues

A residue or fault indicator is an electrical signal that indicates the inconsistency between the observed data and the predictions of a model. It can be used to identify errors in the data, the model, or both.

Tailings generation

The residues generated using the redundancy approach are based on the system's nominal operating input and the measured output. The evaluated redundancy can be considered as the dynamics of the input-output relationship. In the case of a fault, this relationship is never satisfied, and non-zero residues are generated. These residues are used to make the appropriate decisions, such as determining the time of occurrence of the fault and locating the origin of the fault. The fault decision logic component assesses the residues, as shown in Figure 2 [23].

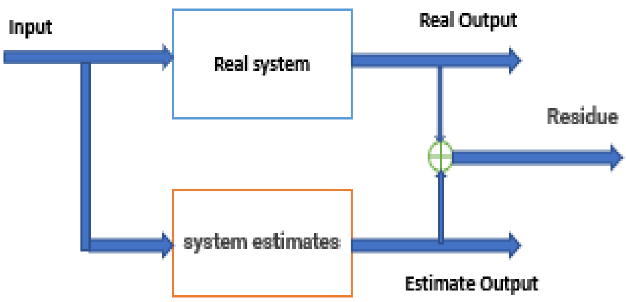

Fig. 2. Explanatory diagram of the ARR method

Residue = real output – estimated output.
If Residue = 0 → No defect.
If Residue ≠ 0 → defect detection.

Assessment of residues

In the absence of a defect, the residue converges to a value close to or equal to zero. However, after the occurrence of a defect, the residue leaves this value in a significant way. This is because the residue is related to the difference between measured outputs and their estimates. When a defect occurs, the measured outputs will change, and the residue will reflect this change [24].

Simulation and results

This section presents the simulation of a stand-alone PV system with backup batteries in MATLAB/Simulink environment under standard test conditions (STC). The system consists of two Soltech 1STH-215-P panels, a DC-DC converter controlled by a perturb and observe (P&O) MPPT, and a bidirectional converter for charging and discharging the battery bank. The system diagram is shown in Figure 3, and the technical specifications are listed in Table 1.

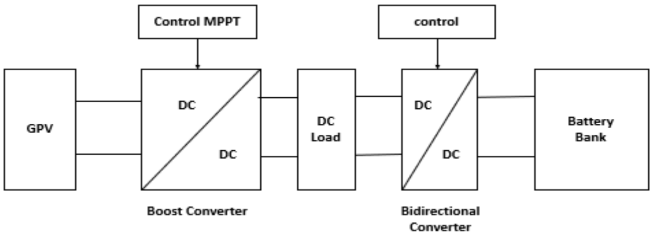

Fig. 3.Diagram of simulated stand-alone PV system

Table. 1. Parameters of the photovoltaic installation

Item	Parameter	Specification
STC	Temperature Irradiance	25 C° 1000 W/m2
PV panels	Maximum power (Pmax) Voltage at maximum power point (Vmp) Open circuit voltage (Voc) Short circuit current (Isc)	213.15 W 29 V 36.3 V 7.84 A
Batteries	Capacity Rated voltage Maximum acceptable voltage level Minimum acceptable voltage level	300 Ah 24 V 29.4 V 23 V

The simulated solar irradiation over time is presented in Figure 4. Figure 5 shows the PV panel's output power and load power. Voltages and currents of both PV panels and the DC/DC converter are respectively shown in Figure 6 and Figure 7.

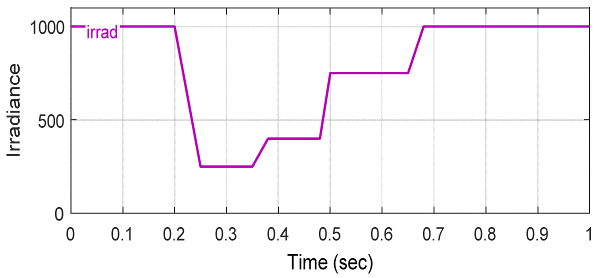

Fig. 4 Simulated Solar irradiation in function of time

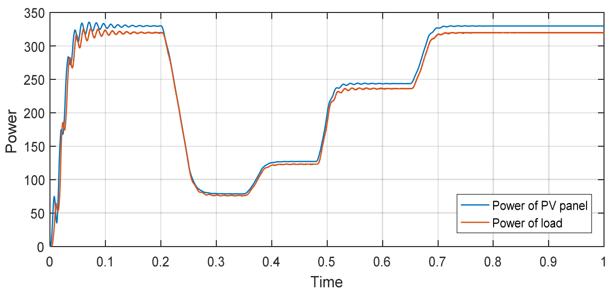

Fig. 5 GPV and Load powers.

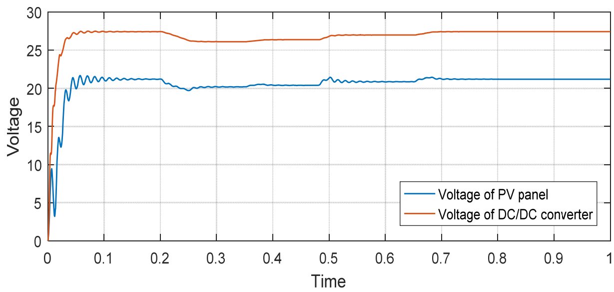

Fig. 6 GPV and DC/DC converter voltages.

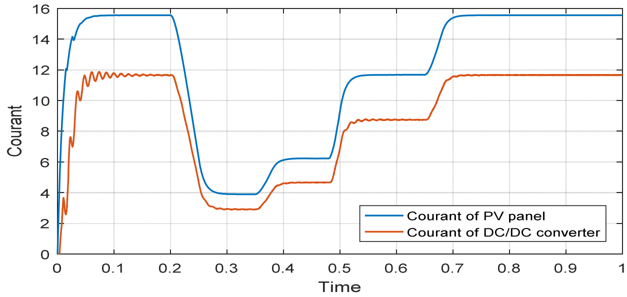

Fig. 7 GPV and DC/DC converter currents.

Shading faults

Partial shading occurs when one or more PV cells in a solar panel are exposed to a lower level of sunlight than the rest of the cells. This can be caused by temporary or permanent shading [25]. In this study, we simulated partial shading for one panel at two different times: 0.3 to 0.35 seconds for 75% shading, and 0.5 to 0.65 seconds for 25% shading as shown in Figure 8. The effect of shading on the output power of the solar panel compared to the predicted output power is illustrated in Figure 9. The ARR of the output power due to partial shading is presented in Figure 10. The alarm triggering for detecting faults related to partial shading is shown in Figure 11.

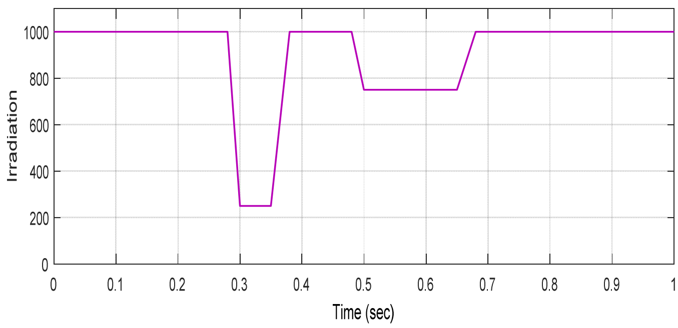

Fig. 8 Simulated shading on panel 1

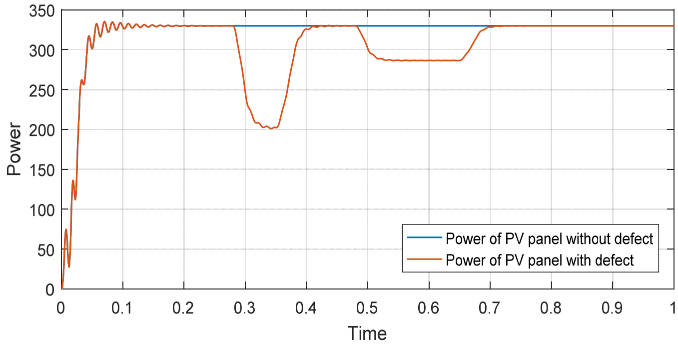

Fig. 9 Power of panel without/with shading defect

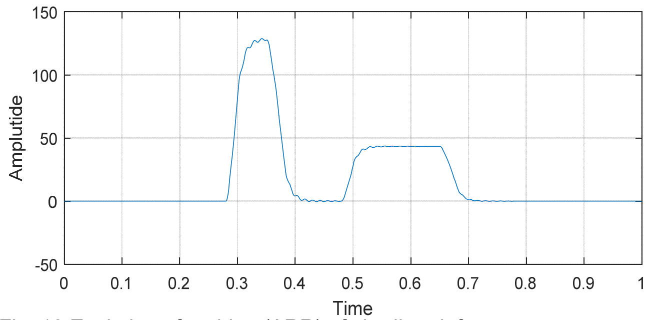

Fig. 10 Evolution of residue (ARR) of shading defect

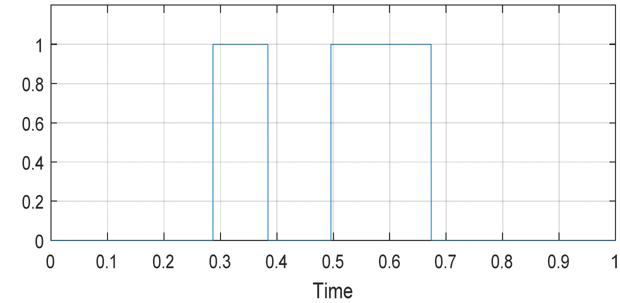

Fig. 11 Detection of shading defect

Breakdown diode

A breakdown diode is integrated into each branch of a solar panel to protect it from negative currents that can be generated during parallel connections of multiple panels. This component can be defective, absent, polarity inversed, not properly connected, or short-circuited. To cover this case, a diode absence fault was created at 0.2 to 0.3 seconds. The effect of the breakdown diode on the output power of the solar panel and the load, compared to the predicted values, is presented in Figures 12 and 13, respectively. The ARR of the breakdown diode defect is illustrated in Figure 14, and the alarm triggering is shown in Figure 15.

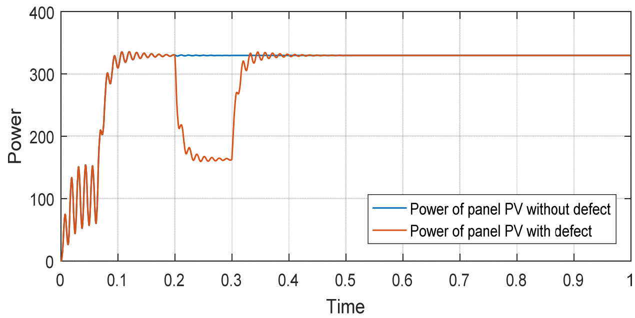

Fig. 12 Power of panel without/with breakdown diode defect

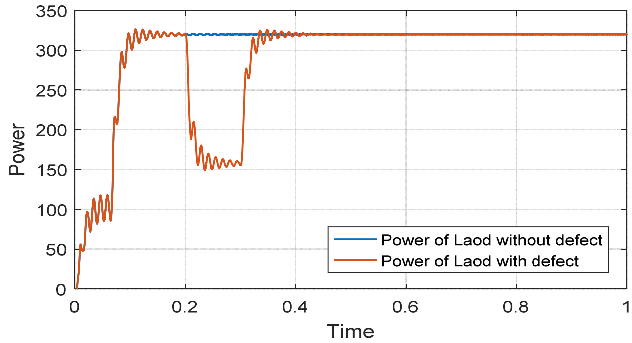

Fig. 13 Power of load without/with breakdown diode defect.

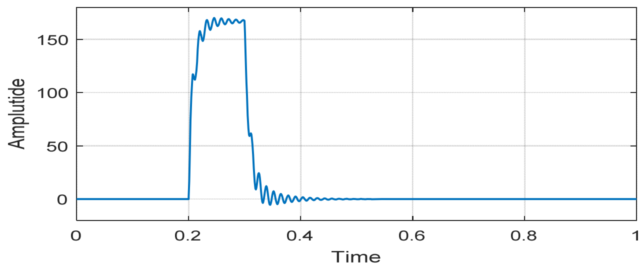

Fig. 14 Evolution of residue (ARR) of breakdown defect.

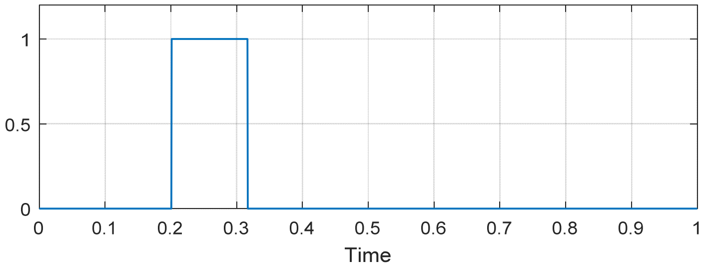

Fig. 15 Evolution of residue (ARR) of breakdown defect.

DC/DC converter faults

The DC/DC converter is an electrotechnical component consisting of several electrical and electronic components. Switch failures are classified into two categories: open circuit (OCF) and short circuit (SCF) [26]. In this study, an OCF defect was created in the switch at 0.2 to 0.4 seconds. The effect of the OCF switch on the power of the load, compared to the predicted value, is illustrated in Figure 16. The ARR of the defect is illustrated in Figure 17, and the alarm triggering is shown in Figure 18.

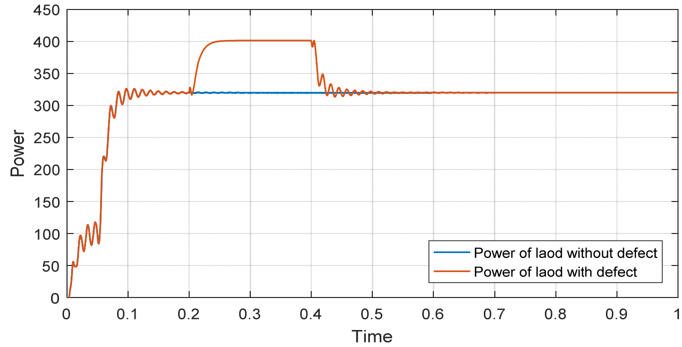

Fig. 16 Power of load without/with OCF defect

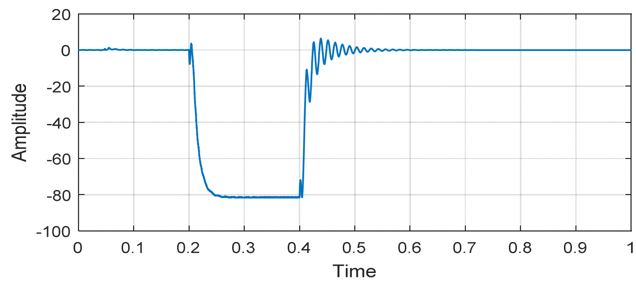

Fig. 17 Evolution of residue (ARR) of OCF defect.

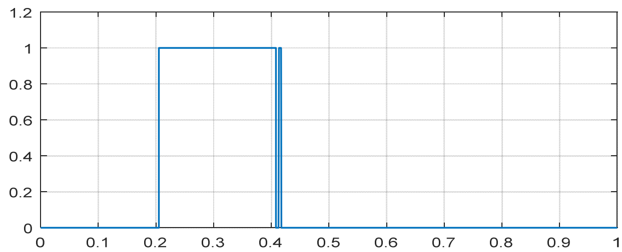

Fig. 18 Power of load without/with all defect.

Conclusions

This work has primarily focused on detecting faults in a stand-alone PV system by simulating various defects. The objective was to develop a diagnostic structure capable of detecting all defects using the ARR method. The proposed approach was evaluated and validated using a MATLAB/Simulink simulation model. Various types of PV installation defects, such as partial shading, breakdown diode, and DC/DC converter faults, were simulated and detected accurately. The obtained results demonstrated the effectiveness and accuracy of this method in detecting faults, which could potentially enhance the fault diagnosis of PV systems, leading to more efficient maintenance and improved system performance.

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