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Identification of Faulty Operation in Photovoltaic Panels

Cristian-Gyozo Haba*

Gheorghe Asachi Technical University of Iasi, Iasi, Romania

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ABSTRACT

Increasing the efficiency of photovoltaic panels (PV) is one of the important goals of researchers worldwide in the field of renewable resources. The important results obtained in the case of finding new materials for the manufacturing of the panels to obtain the highest possible conversion efficiency must be doubled by research for developing methods for efficient real-time monitoring of PV operation in order to rapidly or in advance identify possible failures.

This paper looks for some types of failures and how they can be identified as quickly as possible from the information coming from different sources, the most important being the PV monitored parameters, the PV control system parameters, and from different cloud services.

One way to identify different types of failures is to use machine learning (ML) methods. In applying these methods, an important thing is the availability of a great number of good training data sets. In order to obtain such data sets, this paper aims to create a model of PV using Matlab, which is fed with both real data and data synthesized using fault models. A number of four simulation cases were considered which take into account the normal operation of the photovoltaic panels, their malfunction due to a failure (two different types of failures were considered), and the malfunction of the panels due to the appearance of the two types of failures simultaneously, using input data that was partially measured and partially generated in Matlab. The outputs of these model simulations will be used for training the ML model.

*Corresponding Author

Email: cghaba@tuiasi.ro

Tel: +40-721-696134

1. Introduction

Most current methods of energy production use solar energy directly or indirectly. Fossil fuels such as oil, methane gas, or coal are biological materials from the past that have been turned into combustible materials. Hydro, wind energy, bioenergy, wave energy are also energies created by solar energy.

Photovoltaic energy is one of the energies from the sun that is transformed directly into electricity. Photovoltaic systems convert solar energy into electricity, thus eliminating intermediate stages of transformation characteristic to other energy sources. The conversion of solar energy is done in photovoltaic cells in which the fall of light creates an electric field that releases electrons from the valent bonds, becoming free electrons that determine the process of electrical conduction.

Recent technological advances have led to the emergence of new materials that have significantly increased the efficiency of the conversion process compared to previous technologies. However, the efficiency of converting solar energy into electricity is still quite low compared to the efficiencies of other types of conversion. Therefore, it is necessary to keep this efficiency as possible at the initial level, considering that there is a normal degradation of the characteristics of the photovoltaic panels.

The efficiency of photovoltaic panels is influenced by several factors, the most important being the intensity of solar radiation, the ambient temperature, the state of light conduction of the protective layer, the degree of aging, etc.

Solar panel operation can be affected by environmental factors [1-3]. We generally think of situations in which they affect the part that allows conversion into energy.

Failures can occur throughout the entire day, but the effect of some of them can be detected only after several hours. For example, a fault at the positioning system can be identified right away if it occurs during the day, whether by visual inspection (wrong orientation of the solar panel with respect to solar radiation) or from control system parameters. However, it may remain undetected if it occurs during the night. The same is true in the case of any other mechanical or electrical faults.

The question is how these faults can be identified as quickly as possible from the information that comes from the PV monitored parameters or the information coming from the PV control system.

This paper studies the most common frequent fault situations in PV operation and the way they can be detected using local or/and external information.

One of the causes that lead to the decrease of the PV panel output is the decrease of the illumination of the panel cells. This decrease may be uniform due to the decrease in illumination coming from the sun, or it may be uneven due to the fact that the panel is partially shaded, which makes some of the cells to be less illuminated. As usually PV cells are connected in series, a reduction in the illumination will determine a reduction of the current through the cell, which would limit the current through the other cells. In order to eliminate this situation, diodes are used to short circuit the affected cells. In [4], the shadowing effect is studied, and an artificial neural network (ANN) based method using 3 ANN networks is proposed to identify the partial shading situation, the shading factor, and the number of cells that are affected by continuously measuring the PV panel output. Other applications of ANN in energy-related topics can be found in [5-7].

A condition for increasing the availability of PV panels is the detection of the faults that occur as quickly and accurately as possible. In [8] is presented a method for detecting two types of faults, those caused by interconnection resistance and those related to partial shading. In order to identify the faults, the operating characteristics of the panels in the fault conditions are determined in order to be compared with those in the normal or ideal conditions. Given the differences that result when a fault occurs (size of the generated power), the authors propose to establish thresholds that, if exceeded, will indicate a faulty panel. The proposed solution compares values measured from the PV panels with values obtained with a model created and run in Matlab. In [9], besides faults presented in [8], are considered other fault types such as shading due to dust, faults caused by

open or short circuit conditions, and faults caused by the lower or higher aging degree of PV components. The methodology for fault detection takes into consideration the comparison between the I-V curves obtained using a Matlab model and the I-V curves measured using a dedicated curve tracer. Each of the considered faults induces a specific change in the shape of the I-V curve, which can be considered as a signature to be used in fault identification.

Meteorological conditions have an important influence on the operation of the PV panels and thus on their output power. Different meteorological quantities have a different impact on the PV output, and in [10] is presented a study that determines the correlation between the output power of a PV panel and different weather measured data. The meteorological data considered include irradiance, ambient temperature, relative humidity, and wind speed, and correlation coefficients are determined for each output/meteorological quantity pair of data. Then, different models are tested to find the best to predict the PV performance.

In the development of efficient PV converter control systems, models were proposed in order to simulate both the PV system power stage and the control circuits implementing the control algorithms [11]. Some models have been developed to study the effect of partial shading on the PV output, and experimental tests were carried on to validate them. In [12], authors started their research with a detailed model with five parameters and then tried to modify it to a simpler one with a direct effect on the computational requirements. Other experiments are presented in [13], where PV devices of different types (monocrystalline, polycrystalline, and Amorphous Si) were considered. Data for the PVs and the shading effect simulated in Matlab were compared with experimental data obtained when replicating the experiment on the real PV panels. The model used is based on the example provided by Mathworks [14].

2. Partial Shading

Partial shading is one of the common conditions in PV operation that reduces output power. The main problem is that in order to obtain higher voltage values at the output of a PV system, several PV cells must be connected in series. Because of this, the current that will pass through the inserted cells will be determined by the cell having the lowest current. Given the I-V operating characteristic of the PV cell and the fact that it depends on the level of radiation incident to the PV panel, if one of the cells is shaded, the current through it will decrease, which will lead to a decrease in current also in the other cells. Also, a large amount of power will be dissipated in the shaded cell. So, to reduce this effect, bypass diodes are used, which are connected in parallel with the PV cells but with opposite polarity so that when the current drops below a certain limit, the respective cell is bypassed.

The shading of PV cells can have various causes, the most common being the coverage with dust, mud, or snow. In some situations, partial shading can occur due to the temporary blockage of solar radiation by branches, leaves, and plastic films. A special case is when the panels are in the proximity of buildings that at certain moments cast their shadow over the PV panels, partially or totally covering some of the PV cells.

3. Tracking Sun Position

Achieving a high efficiency of the solar energy conversion involves orienting the panels so that they capture the largest amount of solar energy [15,16]. This generally involves tracking the sun if it is visible (and not covered by clouds) or orienting the panels so that most of the diffused and reflected solar energy is captured. There are currently three configurations in which solar panels operate:

- Fixed panels. In this case, the panels have a fixed position for long periods. Their position is determined based on an analysis of the lighting characteristics considered for at least one year. Some constructive variants allow changes at certain time intervals (every few months) so as to increase the amount of energy captured [17];
- Panels with single-axis tracking system [15,18];
- Panels with two-axis tracking systems [15,19].

Considering the last two solutions, it is obvious that the third configuration will be able to position the panel so as to capture the largest amount of energy. When choosing one or the other of the variants, the aim is to achieve a balance between the amount of additional energy captured and the initial cost of investment plus the energy consumption required for the operation of the panel tracking system. The supplementary costs of a solar tracking system are different for the two solutions. Last but not least, it must be considered whether such a solution can be adopted (see the case of mounting panels on the roof of a house).

Sun tracking can be done using different approaches, including sensors to determine sun position or systems that compute sun position using well-known equations, either in an open-loop or closed-loop architecture.

Equations (1) - (3) can be used to compute declination (δ), elevation (α_s) and azimuth (γ_s) angles of the sun if we know our position on the globe and the moment we need the sun's position (day of year and local time) [15]. The equation for the azimuth can be corrected by taking into account the difference between the solar time and the local solar time.

$$\delta = 23.45^\circ \times \sin \left[360^\circ \left(\frac{n - 81}{365} \right) \right] \quad (1)$$

$$\alpha_s = 90^\circ - \Psi - \delta \quad (2)$$

$$\gamma_s = \cos^{-1} \left[\frac{(\sin \alpha_s \sin \Psi) - \sin \delta}{\cos \alpha_s \cos \Psi} \right] \quad (3)$$

where n is the n^{th} day of the year, Ψ is the latitude.

Knowing the sun's position, the control system can take action to orient solar panels to match this position at every moment.

If we neglect the dispersion radiation and consider that the sky is clear, the maximum PV output will be reached if the panel is oriented towards the sun (the direction of solar radiation is perpendicular on the panel surface. Any deviation from this position will reduce the amount of radiation that reaches the panel.

3.1. Problems in Sun-Tracking Systems

The following problems could arise related to tracking systems:

- Problems related to the method of sun-tracking;
- Problems related to failure in the mechanical system of the tracking system (misalignment, faulty initial position), additional friction force;
- Problems related to electrical motors used for panel positioning.

An example of the problem in the first category is related to the method of detecting the return position. According to the method on which the DAGER system [20] is based (this system is used in the PV panels of the PV system used for this study), the system returns to its initial position at the end of the day, when the light intensity is lower than a certain level. This situation can also happen in the case of some days/periods of a day when, due to the meteorological conditions (darkness occurs due to the arrival of a heavy storm), the brightness decreases so much that, even in the middle of the day, it seems that it is getting (the evening) dark. This can lead the sun-tracking position control system to assume that it is the end of the day and thus elaborates a command for the panel to move to the next day's initial position where the system will wait for the sunrise. Such a condition will result in a non-desired movement requiring additional power consumption. After several minutes/hours, when the weather conditions return to normal and we have normal daylighting (after the storm), the system will have to reposition itself in the position of maximum light intensity.

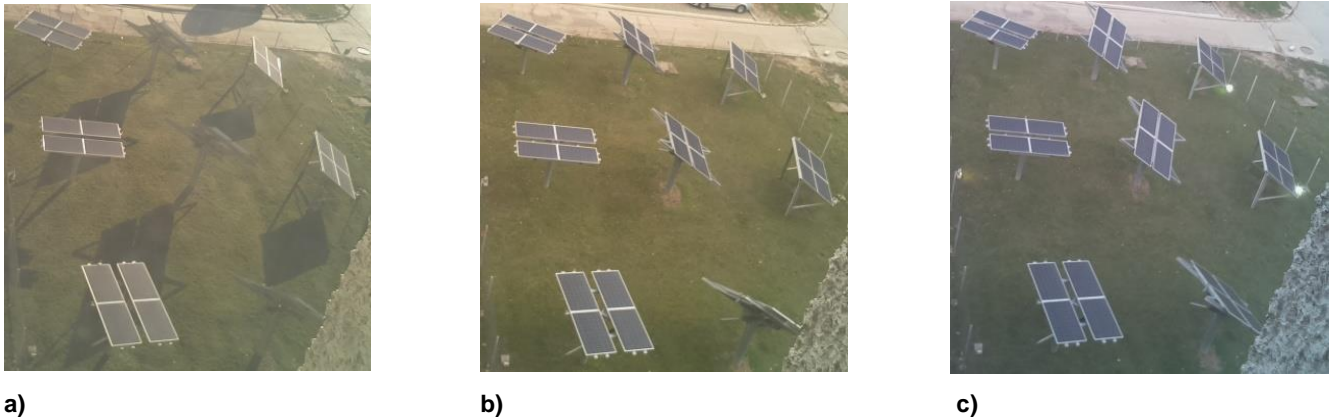


Figure 1: PV position at different times of day: a) sunrise, b) daytime, c) sunset.

The results of other types of failure in the mentioned categories can be seen in Figure 1, where we are given snapshots of a system at different times of the day (sunrise, daytime, and sunset). The pictures were taken for the system considered in the present study. Take into account that the first row of PV panels have a fixed position. Notice that on the second row, where PVs have single-axis sun-tracking systems, the closest one of the panels has a different position than the other two. At the same time, the panels on the third row, which have dual-axis sun-tracking position systems, have different positions and these positions are unrelated to the sun position (as compared to the other PV panels).

This brings into attention that there can be different levels of achieving sun position tracking even if there are single or double axis sun tracking position systems:

- Panel tracks sun position (at the level permitted by single-axis movement);
- The panel is slightly out of sun position tracking (either for single or dual-axis movement);
- Panel's position is totally out of sun-tracking (either for single or dual-axis movement);
- The panel is blocked in one position.

Each of these situations will decrease the PV panel output with respect to the ideal one when the panel is oriented so that the solar radiation is perpendicular to the surface of the panel.

4. Material and Method

4.1. Photovoltaic System

In our research, we considered the PV park existent at the Faculty of Electrical Engineering in Iasi. The photovoltaic park is an installation with a capacity of 9000 Wp using 36 PV panels with a power of 250Wp each, mounted on nine metal structures of which three are fixed, three are mobile with a single-axis sun-tracking system, and three are mobile, with a dual-axis sun-tracking system. The nine metal structures are placed in an arrangement of 3 rows. Four panels are mounted on each structure so that each structure will have an installed power of 1000 Wp.

Each group of 4 photovoltaic panels belonging to each of the three fixed structures (raw 1) is connected in series, thus obtaining three groups with a voltage of 150.8 V. The three groups are connected in parallel and are connected to a FLEXmax 80 MPPT regulator, which is an integral part of the FLEXpowerONE system regulator and inverter model GVFX3048E 3kW. A set of four batteries (12 V, 220 Ah capacity) are also connected to the same controller for energy storage. For mobile configurations, the same type of connection of 4 panels in series in 3 groups is used, which are then connected in parallel to a FLEXmax 80 MPPT type controller. For the single-axis orientation of the panels, a DEGERtracker 30NT single-axis sun-tracking system is used for each of the three

structures of row 2, while for two-axis orientation, a DEGERtracker 3000NT dual-axis sun-tracking system is used for each of the three structures of row 3.

Inverter settings, data monitoring, and modification of control algorithms of the inverters can be modified using a MATE device. The device can connect several inverters using a communication and system management hub. Data can be accessed and displayed remotely if the hub is connected to the Internet. The following type of data can be obtained via the MATE device:

- data related to PV panels operation and energy conversion;
- data related to energy storage in battery and battery status;
- data regarding energy transferred from the power grid;
- data regarding energy transferred to the power grid;
- data about configuration, communication settings, hardware, and software version of the system components.

All this data can be read on the MATE device display or accessed using a web-based interface provided by the MATE device. The information is organized into different categories displayed on several web pages.

An extended architecture of the system that includes the data collecting and processing part is given in Figure 2. As we can see, a set of sensors are mounted on the photovoltaic panels or other elements from the photovoltaic park to measure temperature, humidity, and solar radiation, thus providing local information on the environment in which the panels are operating. Additional information can be collected from weather stations located within the solar PV park or in the nearby region in order to infer the values of weather conditions when local sensors are not available or are out of service. Another link is between the PV system and cloud services that can provide data to be used in the prediction algorithms (weather or astronomical services) for data fusion, integration and processing, and for data storing. These services can also include dashboards that can display and share system operation data in different formats.

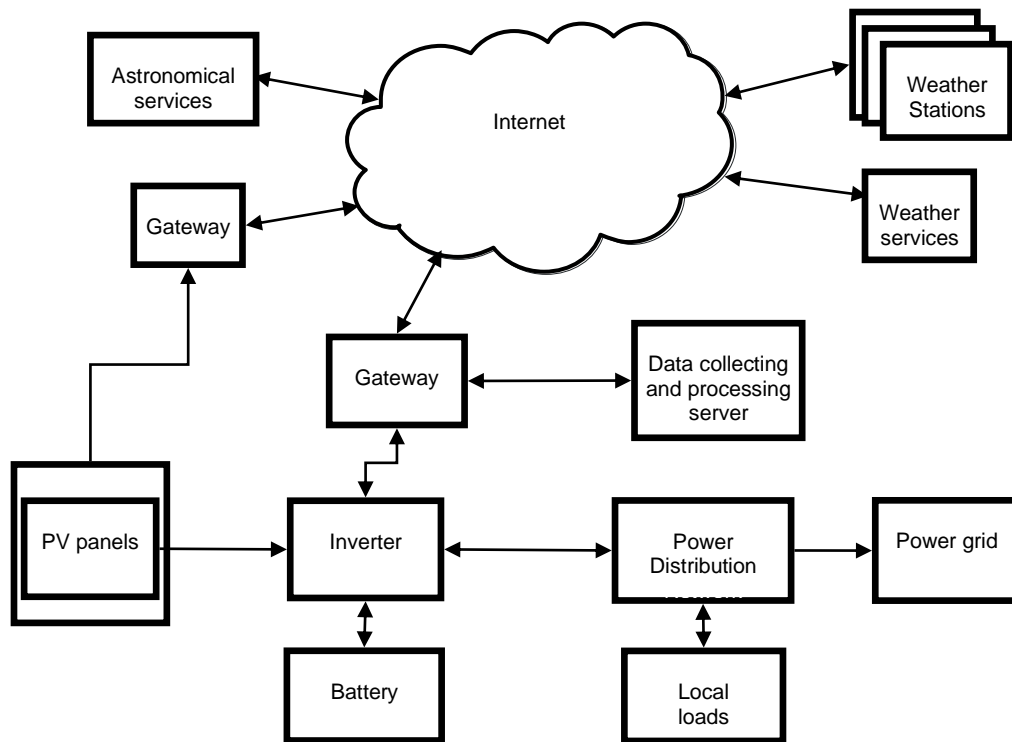


Figure 2: Photovoltaic system with monitoring and analyzing system connected to the grid and to Internet.

In this study, we are interested in accessing services for data about temperature, humidity, precipitations, meteorological conditions (rain, storm, snowing), and sun position calculations that can influence PV output power.

The first system implementation for collecting and processing data from inverters and charging controllers for solar panels was based on a PC running the CentOS operating system.

Due to power outages in the building hosting the PC, a large amount of data has been lost, making data analysis difficult, if not impossible.

In order to solve the problem and reduce power consumption, the data collection application was implemented on a Raspberry Pi (RPI), whose power consumption is much lower and can be powered for backup from a USB power bank.

Ordinary power banks are not designed to be loaded and deliver load simultaneously. As a result, a special power bank was used usually found in the CCTV application.

A camera was also connected to the RPI in order to take pictures of the PV system. The camera was tested in two types of use cases.

In the first case, pictures were taken every one minute for two to three days. The idea was to have an overall image of how the mobile PV panels are positioned by the control system in the attempt to track the sun and also to discover possible shadowing or failure conditions that can be visually detected Figure 1.

In the second use case, the camera is pointed to the sky to determine whether the sky is clear or cloudy. If the sky is cloudy, it is possible that panels are not oriented with respect to the sun position (the sun is not visible) but in the direction of maximum dispersed and reflected radiation. In this case, misalignment with the sun position cannot be considered a failure.

Another direction of study aims at creating a system in which an RPI will be used to implement one sensor node which will communicate with the central system using a wireless connection.

In the testing stage, the sensor node will be mounted on a solar panel with dual axes tracking system and will include a series of sensors for environmental parameters monitoring and for detecting the position of the panel. The sensor node will include light sensors for tracking the sun, a 3-axis accelerometer for determining the position of the solar panel, temperature and humidity sensors for measuring temperature and humidity of the environment, knowing that temperature influences the conversion process and humidity can cause the appearance of dew or frost.

4.2. Collecting Data

The measured environmental data will be compared with the data collected from the local weather stations that publish data continuously on the Internet free of charge.

Data from the PV control system and the other services on the Internet are read every minute. We must nevertheless consider that data on Internet has a different refreshing rate, depending on the service (5min, 10min, 15min or lower).

4.3. Simulation

The simulation was done to analyze the effect of different fault conditions on the output power reduction. The model was created as a combination of models presented in [14, 21]. The PV module is modeled as three strings, each string containing 20 series-connected cells and having in parallel a bypass diode to take into account the shadowing effect or a damaging condition. The power stage of the model is given in Figure 3. The shading effect is simulated by providing different shadowing profiles to one or more cell strings. The shadowing profile can be

given using a shadowing function created in Matlab or using the Signal Builder blocks where the profile is imported from a data file in .csv or .xls format.

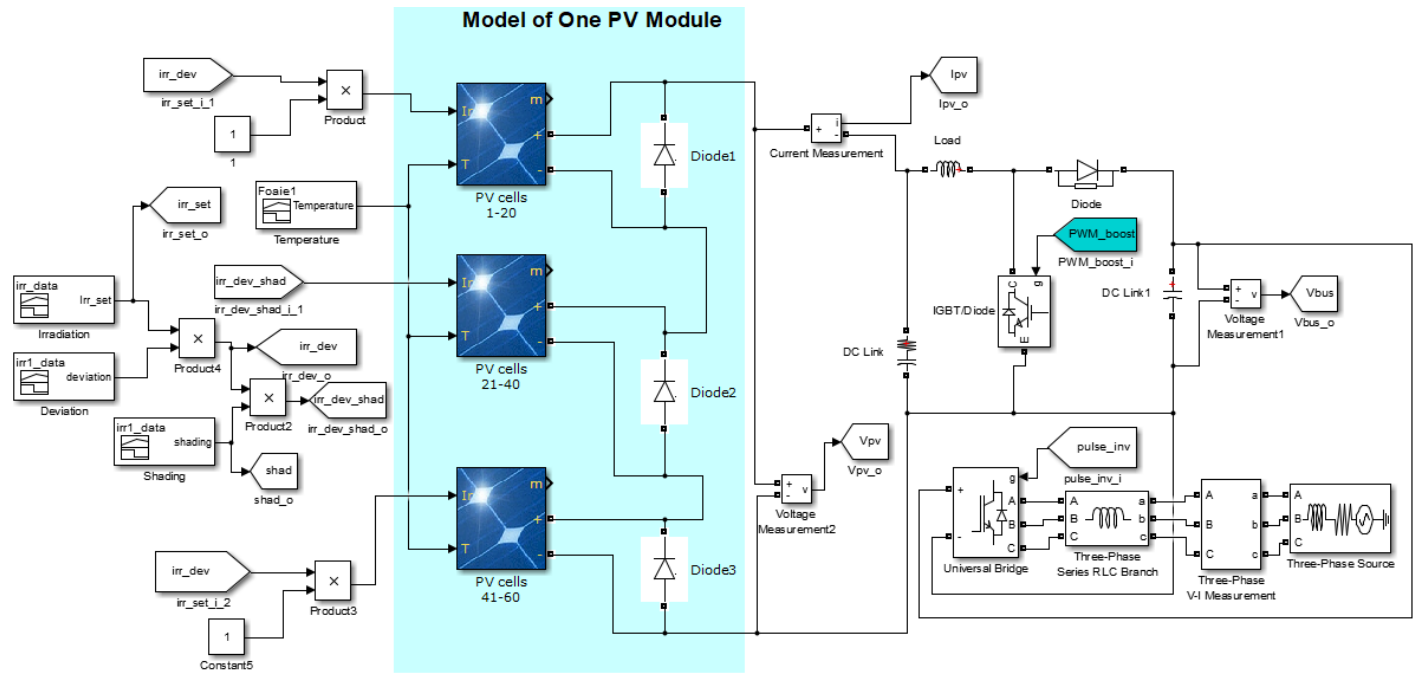


Figure 3: Power stage of the PV system.

In our initial simulation, we have used Signal Builder blocks to simulate both shading effects and panel positioning failures. In the latter case, it is taken into account that a wrong positioning in relation to the maximum irradiation position will decrease the output power. Various situations corresponding to the two types of positioning systems (with one axis and two axes) were simulated. For this purpose, an illumination profile corresponding to measurements made during a day was considered. This profile will be considered the profile for maximum illumination, assuming that the panel is positioned to use the entire solar radiation. The deviation from this maximum value will be modeled by applying a function of diminishing the radiation, the function being particular to the type of failure.

In the case of single-axis sun tracker panels, the orientation of the panels will be on a single axis, the sun being followed from sunrise point to sunset point. The tilt angle will be the same, with only the azimuth angle changing. With this in mind, the radiation received by the panel will be maximum at the point where the tilt angle is equal to the elevation angle, and it will be smaller in the rest. The radiation received by the panel can be calculated with the relation

$$R_m = R_i \cdot \sin(\alpha + \beta) \tag{4}$$

where R_m is the radiation at the panel level, R_i is the incident radiation, α is the elevation angle, and β is the tilt angle. The radiation will be maximum when $\alpha = 90^\circ - \beta$. If we fix the panel tilt angle at optimum value α_{opt} , then the radiation received by the panel will be:

$$R_m = R_i \cdot \cos(\alpha_{opt} - \alpha) \tag{5}$$

If due to mechanical problems, there is a deviation of the tilt angle from the prescribed value, then the variation in radiation will be:

$$R_m = R_i \cdot \cos(\alpha_{opt} - \alpha + \theta) \tag{6}$$

where θ is the deviation angle from the prescribed tilt angle.

In [17] are presented different expressions for computing the optimal tilt angle to be used for the entire year or shorter periods (ex. for one trimester or one month).

If we consider panels with dual-axis sun tracking positions, then deviations can appear both in tilt angle and azimuth angle. In this case, the radiation received by the panel can be computed with a more complex expression such as:

$$R_m = R_i \cdot [\cos(\alpha) \cdot \sin(\beta) \cdot \cos(\varphi - \mu) + \sin(\alpha) \cdot \cos(\beta)] \quad (4)$$

where φ is the azimuth angle of the sun and μ is the azimuth angle of the panel.

4.4. Machine Learning Pipeline

In order to monitor and detect different failures of the PV system, a modular ML pipeline was developed to classify solar PV failure by using measured and synthesized data sources (Figure 4).

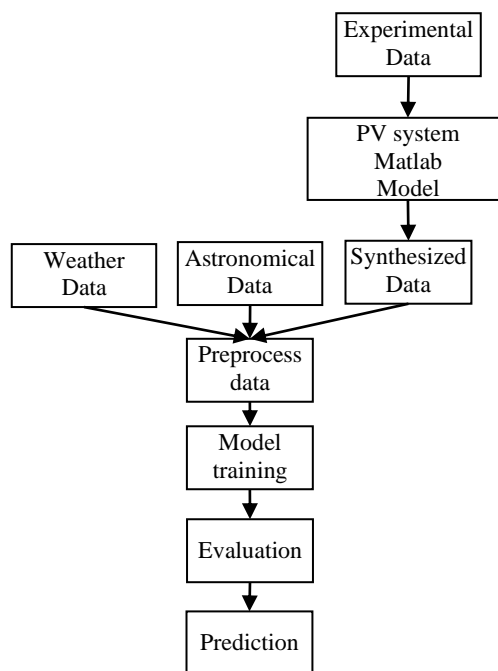


Figure 4: The ML processing pipeline.

The synthesized data comes from the developed Matlab model fed with data from sensors (irradiation, temperature) and with data generated with Matlab models related to different failure conditions (partial shading, misalignment of the panel with respect to sun position).

The pipeline contains a pre-processing stage, model training, evaluation, and prediction.

The training and evaluation stage of the ML pipeline was done using Python in a Python Notebook environment and using Sklearn Library as this was used before in other studies [22].

5. Simulation Results

The method has been tested under varying conditions that simulated different faulty conditions. The considered conditions took into consideration PV panels with both single-axis and dual-axis sun-tracking systems as are available in the PV park that was used for the study.

First, it was considered the case of PV panels with a single-axis sun tracking system for which the output power

was measured for normal operation and deviation from the faulty conditions when there is a deviation from the optimum tilt angle equal to 10°, 20°, and 30°.

The irradiation curves for incident radiation and for radiation at panel level are given in Figure 5. Data for incident radiation was taken from measurements done in the PV park for different periods. For the first simulations, it was considered data corresponding for one day. Panel irradiation is computed considering equation (5) for normal operation and equation (6) for faulty operation. Figure 5a presents the irradiation profile for one day with measurements made every minute. Figure 5b presents the irradiation reduced due to restriction of movement on only one axis for a single-axis tracking system, Figure 5c depicts the profile of the shadowing effect also given for a day, while Figure 5d presents the resulting irradiation.

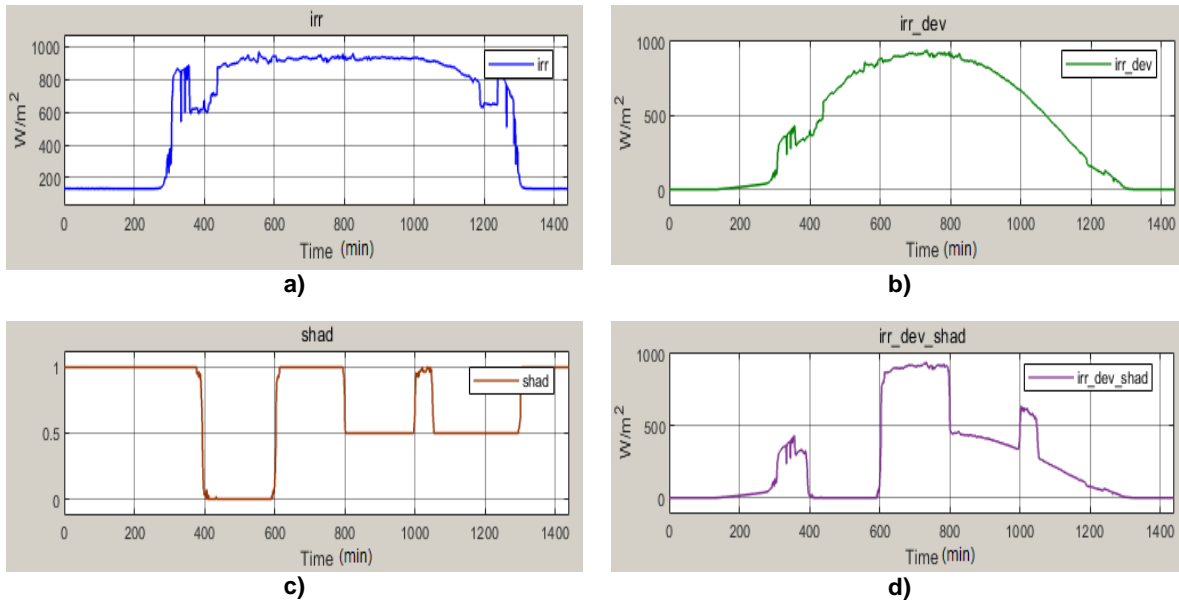


Figure 5: Irradiation (a) Irradiation with deviation (b) Shading profile (c) Resulting irradiation (d) curves.

The profiles of resulting radiation for different values of deviation from the tilt angle are given in Figure 6.

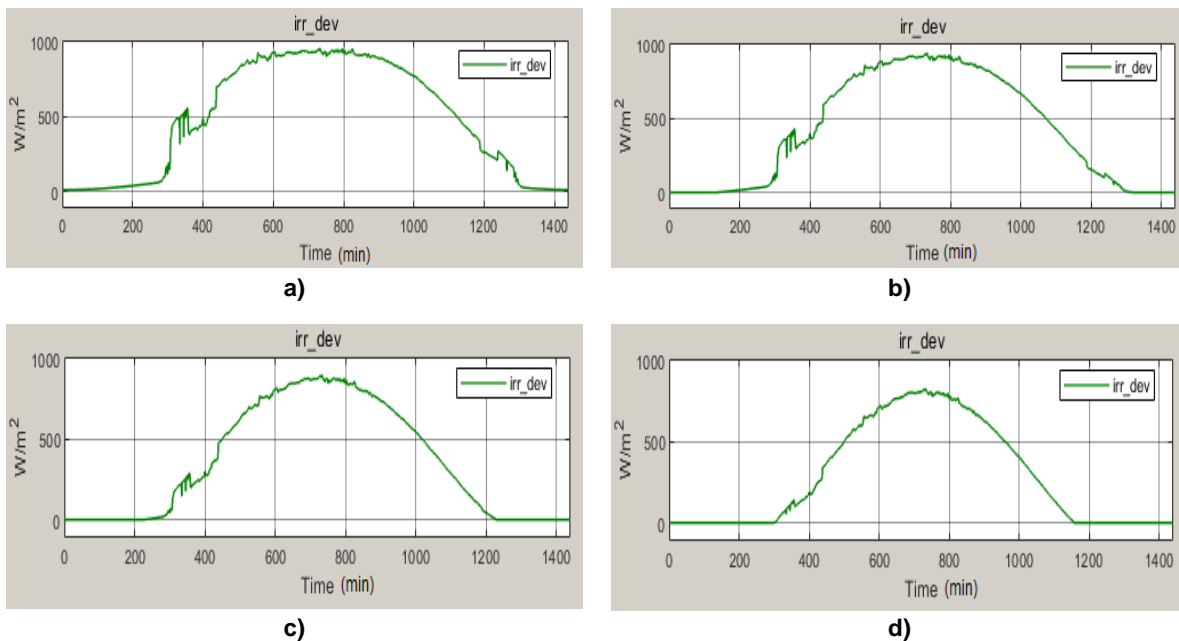


Figure 6: Resulting irradiation for (a) 0°, (b) 10°, (c) 20° and (d) 30° deviation from the preset tilt angle.

The profiles of resulting radiation considering the shading effect for different values of deviation from the tilt angle are given in Figure 7.

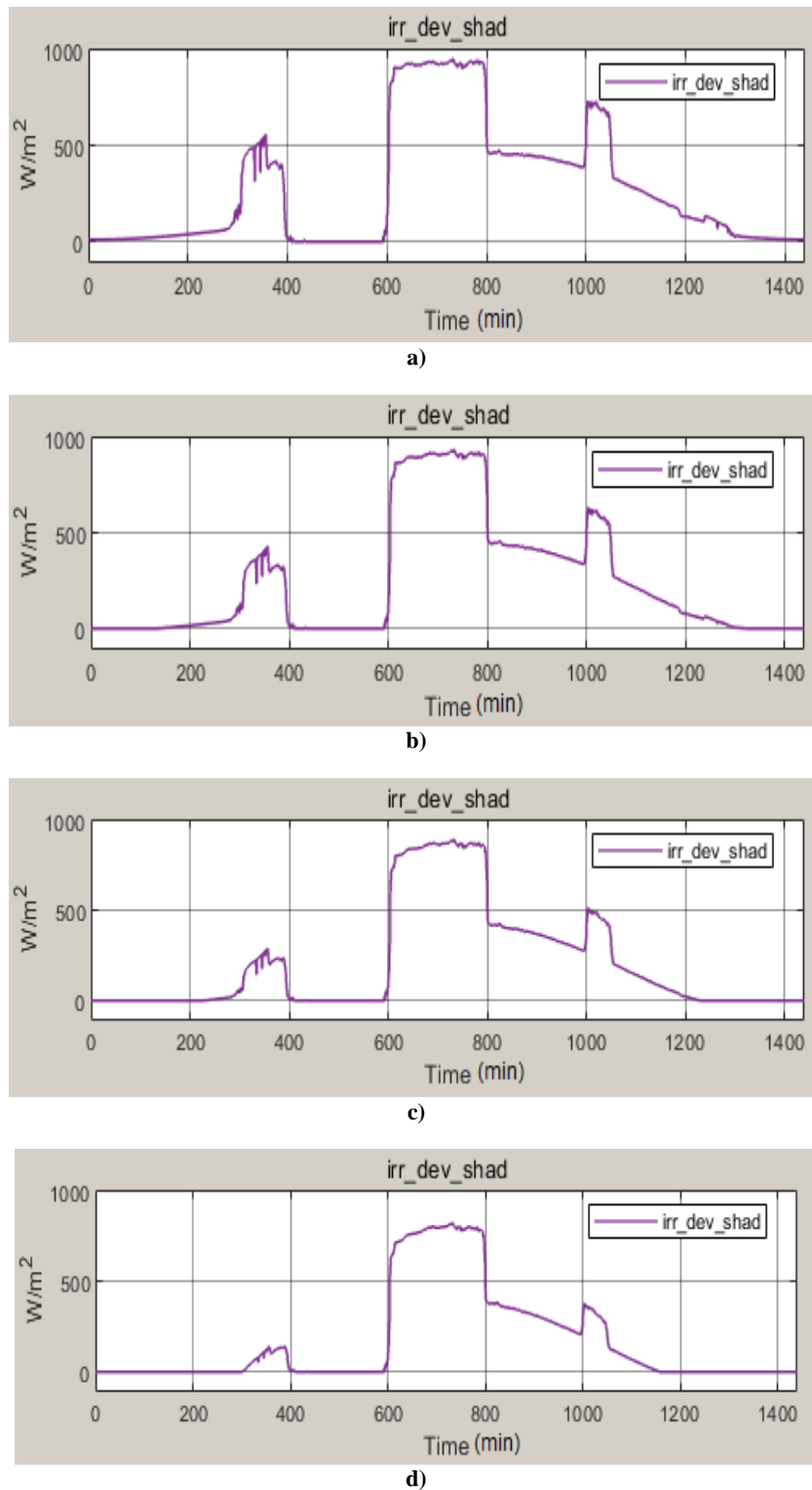
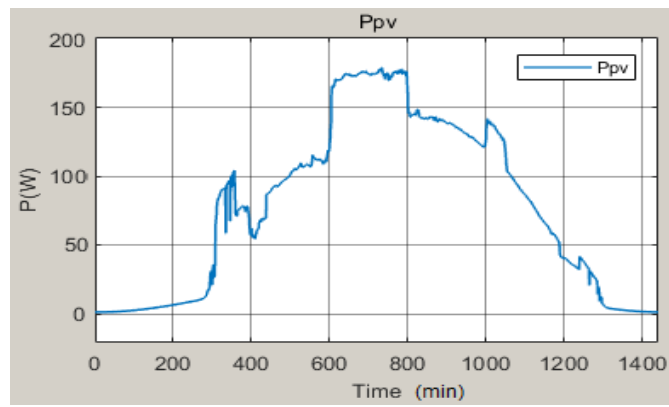
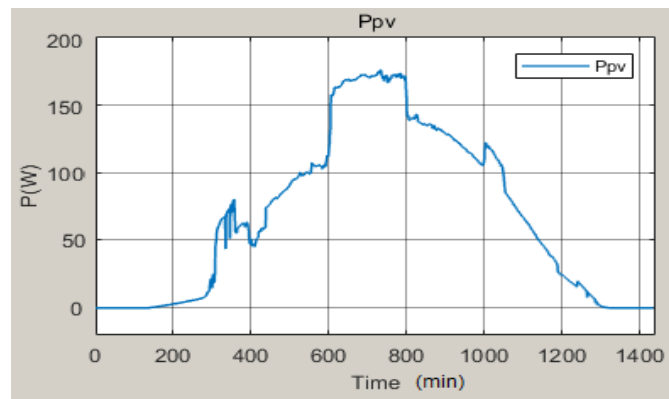


Figure 7: Resulting irradiation for (a) 0°, (b) 10°, (c) 20° and (d) 30° deviation from the preset tilt angle and shading profile.

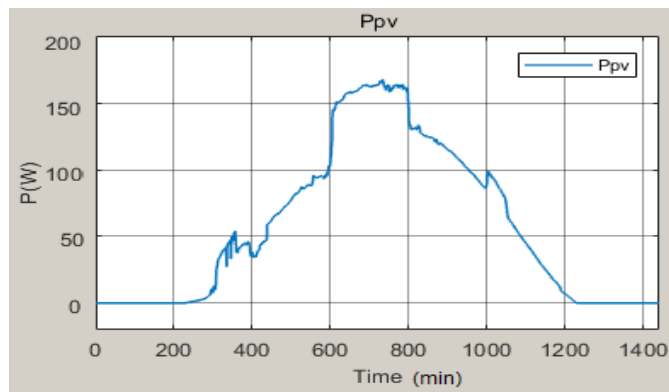
The Matlab model was simulated with the input for irradiation generated as described above, and different sets of generated data were obtained. For example, the PV-generated power is presented in Figure 8 for the case where different deviations of the tilt angle and the same shading profile were used.



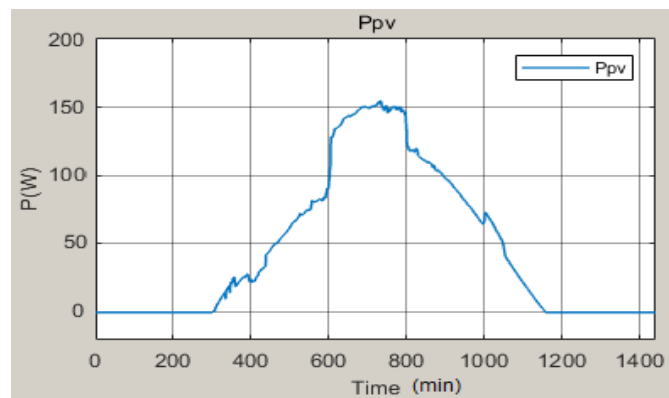
a)



b)



c)



d)

Figure 8: Resulting irradiation for (a) 0°, (b) 10°, (c) 20° and (d) 30° deviation from the preset tilt angle and shading profile.

Data generated using the Matlabmodel, which is used to feed the ML pipeline, corresponds to the same data collected from the PV control system. This includes a timestamp, PV panel voltage and current (I_{pv} , V_{pv}), PV panel output power (P_{pv}), inverter input, and output.

Considering that each metal structure in the PV park has a group of 4 PV panels and a bypass diode is used for each PV panel, we can generate randomly shading conditions as given in Figure (9).

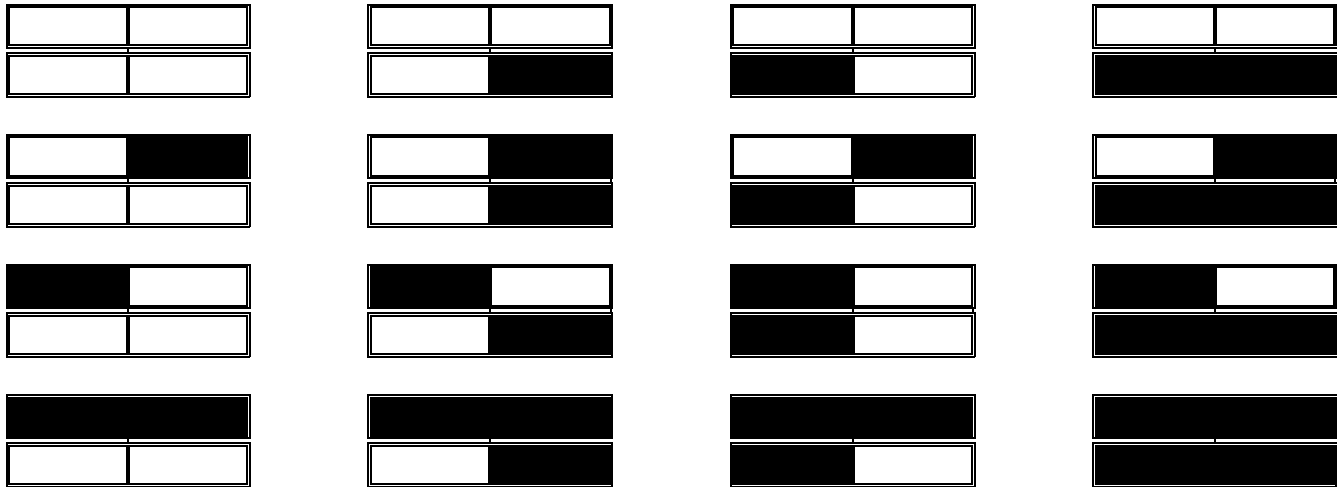


Figure 9: Shading profiles for the 4 PV panel groups.

Shadings can be generated in a Matlab function randomly for each diode bypassed section both for status and duration. Though real shading profiles due to snow or other causes can be more complex, the profiles in (Figure 9) can be considered a first approximation.

The profile generation function can also automatically classify generated data with respect to shading conditions for which the ML system will be trained.

The data for the simulation cases is given in Table 1.

Table 1: Simulation cases.

Case	Days	Seasons	Shading		Deviation		Temperature Sets	Max Irradiation Measurements Per Day
			Present	Sequences	Present	Sets		
Normal	7	2	No	-	No	-	1	1440
Deviation	7	2	No	-	Yes	3	1	1440
Shading	7	1	Yes	3	No	-	1	1440
Combined	7	1	Yes	3	Yes	3	1	1440

In this study were considered four simulation cases, *Normal*, *Deviation*, *Shading*, and *Combined*. The *Normal* case corresponds to the case when the PV panels function normally.

The *Deviation* case corresponds to the situation when there is a deviation of the PV panel from the optimum position with respect to the sun due to unwanted mechanical rotation. When the deviation condition was assessed, the set of three deviation values, 10, 20, and 30 degrees, respectively, was considered.

The *Shading* case corresponds to the situation when the panels are covered mainly with snow; therefore, this case was considered only for the winter season. The *Normal* and *Deviation* cases were considered both for the winter and summer seasons.

The *Combined* case considers that two faulty conditions are present, i.e., shading due to snow and deviation of the PV panel. The shading sequences take into consideration two raw models of snow melting. The first model with two sequences corresponds to the situation when the panel evolves from full covered (all four panels covered) to the half-covered (lower two panels covered), then quarter covered (either left or right panel covered) to finally fully uncovered. The second model corresponds to evolution from fully covered to half-covered and finally fully uncovered.

For each simulation case, the irradiation and temperature values are measured a week in summer and a week (with snow conditions) in winter.

6. Discussion

The present study started from the desire to identify in a PV park the situations when the generated power is affected by situations that reduce the conversion capacity or result in functional failure.

One of these situations is partial shading, and previous studies have sought to apply ML methods to identify them with the particular situation of shading due to snowfall [22] based on data collection and manual classification. Various data sets were collected, but their size and quality were sufficient to achieve rather a proof of concept than efficient training sets for developing well-tested models.

In the following years, these measurements were scheduled to be repeated in the wintertime, but the results were unsatisfactory on the one hand because it snowed very little and on the other hand because, just during the snowing period, the data acquisition system or its connection to the park control system did not work.

At the same time, in the following period, a series of failures appeared at the studied PV park. They included failures related to the control system, mechanical failures of the sun-tracking systems, or failures of the energy storage system (batteries).

Since the replication of these types of failures is costly and also due to the fact that the weather conditions affecting the PV park power output cannot be controlled, a model of PV panels in Matlab was sought in order to simulate such conditions. The data obtained during simulations, together with real data, are then intended to be used in the training stage of the ML models.

Given that the training efficiency of ML models increases with the increase in the number of data sets available and with the number of good features, it was sought to generate and test different sets of features.

The existing PV park at the faculty consists of various types of solar tracking systems (3 panels are fixed, 3 use a single axis sun tracking system, and 3 use a dual-axis sun tracking system). Although this is not a common case in large PV parks, the existence of a fixed PV panel or with different sun tracking systems can be used to monitor other types of panels better.

Specifically, fixed panels can be a reference for estimating the amount of energy that should be converted by the other types of panels. By measuring the energy produced by such a panel and knowing what the resulting decrease is, due to its fixed position, according to relation (5), it is possible to know what should be the output power of the other types of PV panels.

7. Conclusions

Maintaining the output of the PV systems at high levels implies continuous monitoring of different parameters, either of the system itself or external parameters that can influence PV system operation. Identifying possible faulty operations in advance or as quickly as possible after their occurrence helps the maintenance team to intervene, selecting the most appropriate actions for eliminating the failures rapidly.

One way to identify failures makes use of machine learning techniques which require the elaboration of a model for the system, training it, and deploying the model in the system.

Obtaining training sets for some of the possible failures is either a time-consuming or expensive process. Therefore, a solution is to use a combination of real and synthesized training sets. These training sets can be obtained by creating a mathematical model of the PV system and simulating the occurrence of different types of failures. In this paper, two failure conditions were considered, either separate or combined. Simulations were performed for normal operation, operation with a deviation of panel position from optimum, operation under shading condition due to the snow covering PV panels, and the combination of the two conditions.

In the presented application, the PV system is simulated in Matlab and is fed with input data that partially includes measured real data, while the rest of the input data is obtained by simulating the failure conditions.

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