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Soiling Measurement Characterisation System Over a PV Solar Field in the Southern Spain

Soiling PV Characterisation

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Abstract. Soiling is one of the main problems that cause power losses in photovoltaic plants. This article presents a method to determine dirt in a photovoltaic plant using three digital cameras and analyzing the average (Red, Green and Blue) RGB values obtained from each of them. The study also incorporates inclined, global, direct and diffuse irradiance data, as well as suspended particle data PM10, PM2.5 and PM1, where the number indicates the size of the particle in µm. In this investigation, three digital cameras were strategically placed to capture images of the panels at regular intervals. From these images, average RGB values were calculated to quantify the level of dirt on the panels. These values were correlated with solar radiation data, the photovoltaic power of the plant and the concentrations of suspended particles. The results demonstrate that analysis of mean RGB values provides a reliable and non-intrusive method for monitoring fouling in PV plants, contributing to more efficient maintenance strategies and an increase in energy production.

Keywords: Soiling, Photovoltaic, Digital Cameras, PV Production, Solar Energy

1. Introduction

In solar energy systems, the performance evaluation and the energy yield are one of the essential pieces of information to the stakeholders. The state of the system and the amount of energy produced by the system in a specific period, depends on present and past weather conditions, including snow and dust, the efficiency and balance-of-system losses, therefore the modeling of the solar energy systems yield includes several sources of uncertainties [1].

The accumulation of dirt on photovoltaic panels, known as soiling, is one of the main factors that affect the energy generation efficiency in these plants [2, 3, 4]. In areas with high dust pollution, dirt losses can reduce the power generated by up to 30% per day [5]. This phenomenon not only negatively impacts energy performance but also increases cleaning frequency and operating costs.

The energy yield can be estimated by using empirical or physical models with accurate input data. However, most solar systems do not include on-site high-class measurement devices for irradiance and other weather conditions. Furthermore, in many cases, these models have a high computational cost. Nowadays, machine learning techniques (sub-branch of Artificial Intelligence (AI)) are extensively used, including solar energy systems, due to their ability to solve nonlinear and complex data structures and the low computational cost to simulate [6]. However, most of the machine learning models for analyzing the performance of solar energy systems are based on historical meteorological data, with the consequent problems of obtaining historical data of the installation and the non-generalizability of the model.

On the other hand, the growing interest in applying Unmanned Aerial Vehicles (UAV) to monitor and inspect solar energy systems has significantly improved system monitoring and fault detections based on images from the solar energy system [7]. Currently, inspection systems with images (thermal or RGB) can efficiently detect installation failures.

Among all the computer vision techniques, one of the most innovative and fastest growing is Object Detection. Object Detection is the task of classification and localization of objects in an image or video based on machine learning. It has gained prominence in recent years due to its widespread applications [8]. However, there is no evidence that this technique is used for fault detection and performance evaluation of solar energy systems.

For all that, in this proposal a new technique based on images obtained with low-cost cameras or security cameras will be developed. With this, it is expected to solve the problem of generalization of the model to different systems and the difficulty of obtaining long time series of precise meteorological data, having therefore, a methodology capable of determining the degree of soiling of a solar photovoltaic plant, from low-cost cameras, based on the visible spectrum (RGB).

2. Materials and methods

The CIESOL building is the Solar Energy Research Center located inside the Campus of the University of Almería (UAL), in south-east of Spain. The building, with a total surface of 1072 m^2 is split into two floors. Specifically, it is composed of six offices, all of them facing east and located on the ground floor, with the exception of the main office which is located on the upper floor, eight laboratories which face north (four located on the ground floor and the other four are situated on the upper floor), a plant where a high efficiency boiler and an absorption machine are located, and finally, rooms for employees of the centre such as the kitchen and the toilets.

2.1 CIESOL Photovoltaic plant

CIESOL currently has a 9.32 kWp photovoltaic plant in operation, an experimental photovoltaic plant of approximately one kWp for studying the influence of dust deposition on voltage and intensity values, as recorded by each panel, as well as a meteorological and radiometric station.

Fig. 1 shows the one photovoltaic plant on a field of solar collectors for domestic hot water (DHW); these will be characterized to evaluate dust losses.

Figure 1. *CIESOL's photovoltaic and DHW collector plant*

The photograph shows the PV plant (the three upper module rows), installed in 2008 to supply the building's electrical lighting needs. It has a power output of 9.32 kWp and is made up of a total of 42 ATERSA 222 Wp modules each. It should be noted that Almeria, given its geolocation, is an area that frequently experiences Saharan dust phenomena, thus making it an ideal location for the experiments involving module contamination.

2.2 Experimental photovoltaic plant

There is an experimental facility (Fig. 2), consisting of 4 modules identical to those of the 9.32 kWp plant (point 2.1), fully monitored and under constant maintenance since their commissioning.

Figure 2. *CIESOL's soiling experimental photovoltaic plant*

This soiling station will allow subsequent work to calibrate the soiling levels that can be detected in the photovoltaic solar panels.

2.3 Digital cameras for soiling detection

Currently, three low-cost cameras have been installed to continuously monitor natural phenomena acting on CIESOL's 9.32 kWp photovoltaic solar field. The cameras, all identical, can view the panels from a central perspective and from the side. Figure 3 shows the distribution of cameras, where in the red box there is one camera and in the yellow box there are two cameras, each pointing to a wing of the solar PV field.

Figure 3. *Distribution of the cameras for soiling characterisation in the CIESOL's photovoltaic plant*

As can be seen, up to three cameras measuring intensities in the RGB colour space, attending to different positions. Figure 4 shows the images obtained from each of the cameras for 2 May 2024, at 11:40 Universal Time Coordinated (UTC). With these cameras, the aim is to characterise the level of soiling of the CIESOL solar photovoltaic plant, based on the digital levels of the image, centred on the photovoltaic panels. Finally, Figure 4 shows a snapshot of the photovoltaic installation from the three points of view.

Figure 4. *Distribution vision of the cameras in the CIESOL's photovoltaic plant. a) left area of the PV plant, b) view of the right area of the PV plant and c) general perspective of the PV plant*

2.4 Soiling estimation system with RGB channel data

A MATLAB code has been developed to calculate the optimal solar height for each day and next, the images are selected for these moments. After that, a binary mask (0 is black and 1 is white) is applied to each image, in which 1 is the entire part of the PV panels and 0 is everything else in the image (Fig. 5). Once the mask is applied, original imagen and mask are superposed, obtaining only the PV area. With the final image it is possible to make the RGB average of the PV panel.

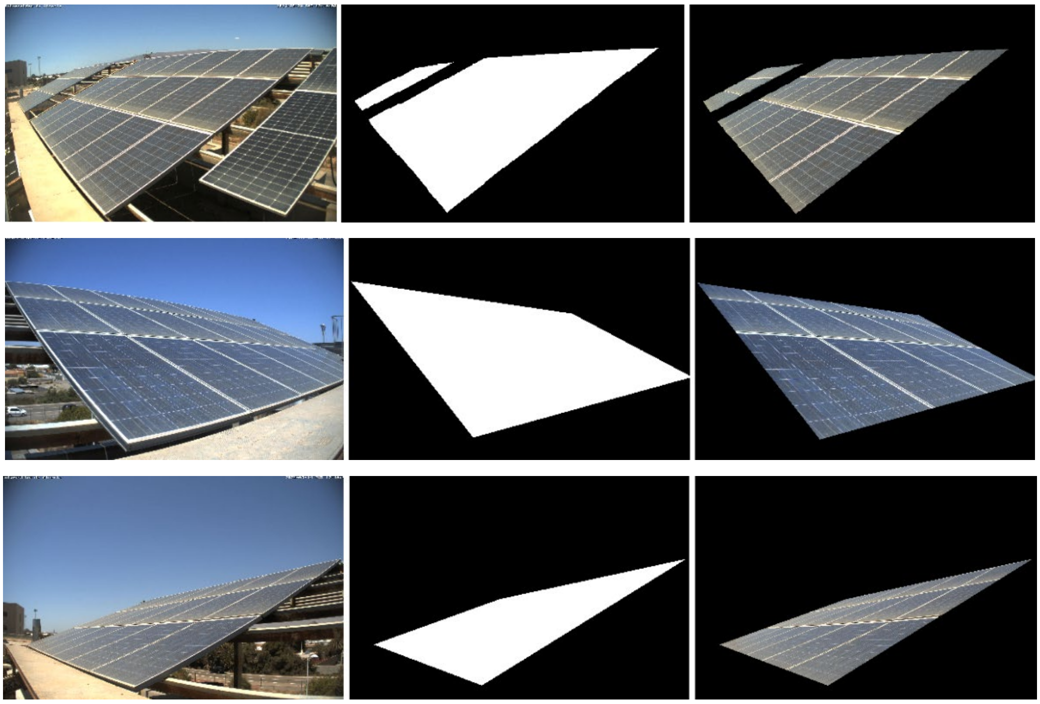

Figure 5. *Masks applied to the PV area from each digital camera view*

This process is repeated every day from April to July 2024. In addition, this is done with the three existing cameras from which the plant can be completely observed or from the left or right side. On the other hand, data on tilted direct, global, and diffuse irradiance have been obtained, as well as photovoltaic power and the RGB averages from each camera applied to the mask. The global tilted irradiance data has been filtered to over 850 Wm^{-2} so that the data used corresponds to the most optimal and similar conditions possible. Although the moments with a value higher than this threshold were filtered, there were several cases where phenomena not typical of a cloudless day appeared; for this reason, the value of the diffuse horizontal irradiance was also included, to know if there were any clouds on the horizon. Once all these variables were obtained, we proceeded to represent them graphically for the time of study.

3. Results and discussion

This section will present the results of the trends observed between the RGB channels of digital cameras and other variables related to the meteorological conditions and the production of the photovoltaic plant. The objective is to be able to have characteristic and representative trends of the fouling level of the solar PV plant. Therefore, the first requirements for this objective are to define behavioral patterns between the digital levels of the digital camera images and the electrical behavior of the panels. For each day, the value of each variable has been used when the solar height is maximum, to consider the highest perpendicularity between the sun and the solar panels. To analyze the trends of the digital levels of the cameras and the production conditions of the panels, we have also included measurements of suspended particulate matter, which may be linked to episodes of haze in the atmosphere. Figure 6 shows the evolution of the average of the RGB channels of the digital camera observing the left half of the photovoltaic panels, together with the data of PV power generated and the concentration of PM10 (μgr m^{-3}).

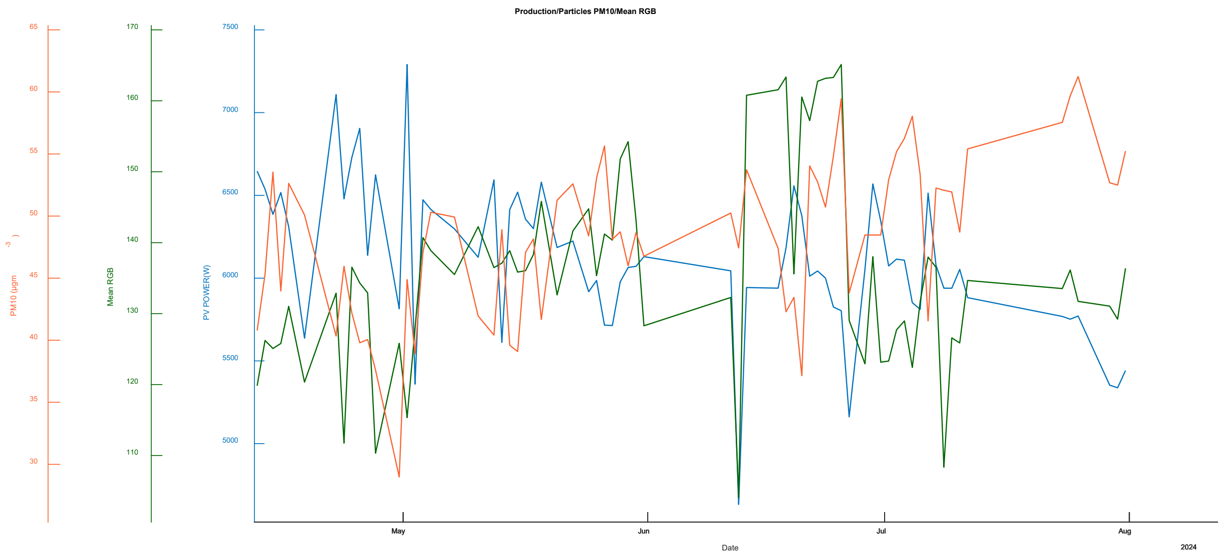

Figure 6. *Temporal Evolution of PV Power, RGB mean and PM10 (left vision)*

Observing the above graph, where the blue line represents the PV power value (W), the green curve represents the average RGB value and the orange line represents the PM10 value, for the moments of maximum solar height of each day analyzed, it can be seen how the trends follow a significant similarity, especially in the behavior between PV production and the average RGB. In addition, it can be seen how the increase in PM10 concentration is linked to a drop in PV production. Nevertheless, in this work the results of the three cameras are presented to see which position could be more interesting when studying the soiling (related to the drop in production and increase of PM10). Therefore, Figure 7 shows the same data as Fig. 6, but considering the right half of the PV solar field.

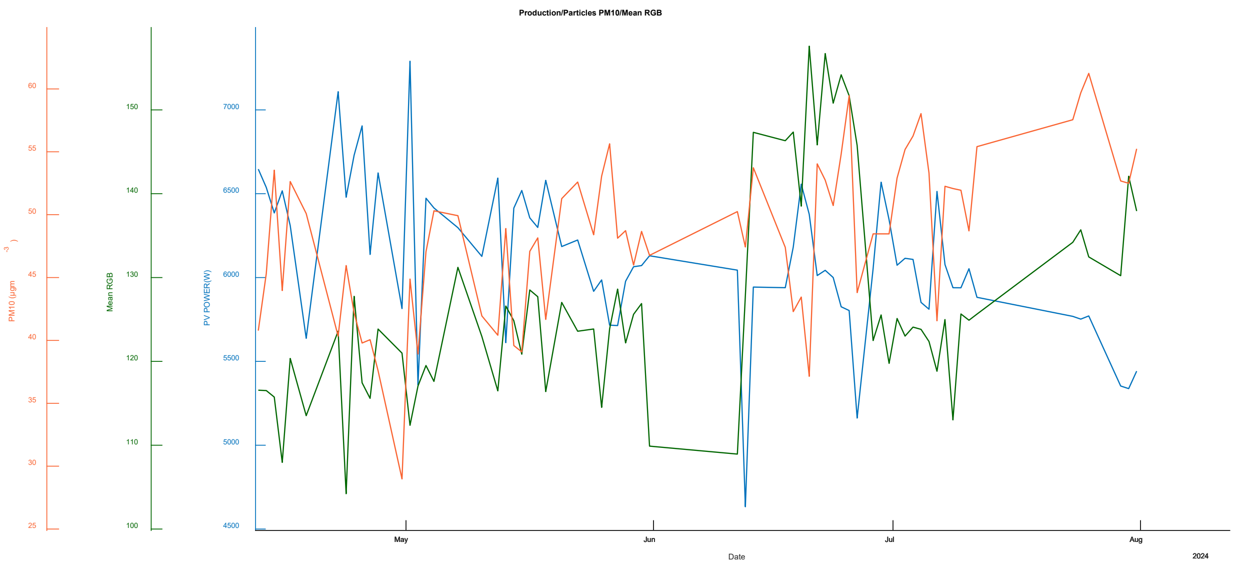

Figure 7. *Temporal Evolution of PV Power, RGB mean and PM10 (right vision)*

The angle of incidence of the sun is an especially important condition for capturing any phenomenon with digital cameras; therefore, having different views of the solar field is something that, a priori, can be interesting. In the graph of Figure 7, it can be observed how the behaviour of the production and PM10 are identical, but already the RGB average, when observing the complementary part of the plant, follows other trends. They are quite similar, but several details mark differences as at the end of May and beginning of June, where the RGB channels seem to follow the PM10 evolution in a worse way, but the similarity with respect to the PV power improves. The remaining camera oversees observing the behaviour of the whole plant from a lateral perspective and, although there are areas with low spatial resolution, the whole PV solar field is covered. Figure 8 shows the trends of this camera compared to the PV output and PM10 levels.

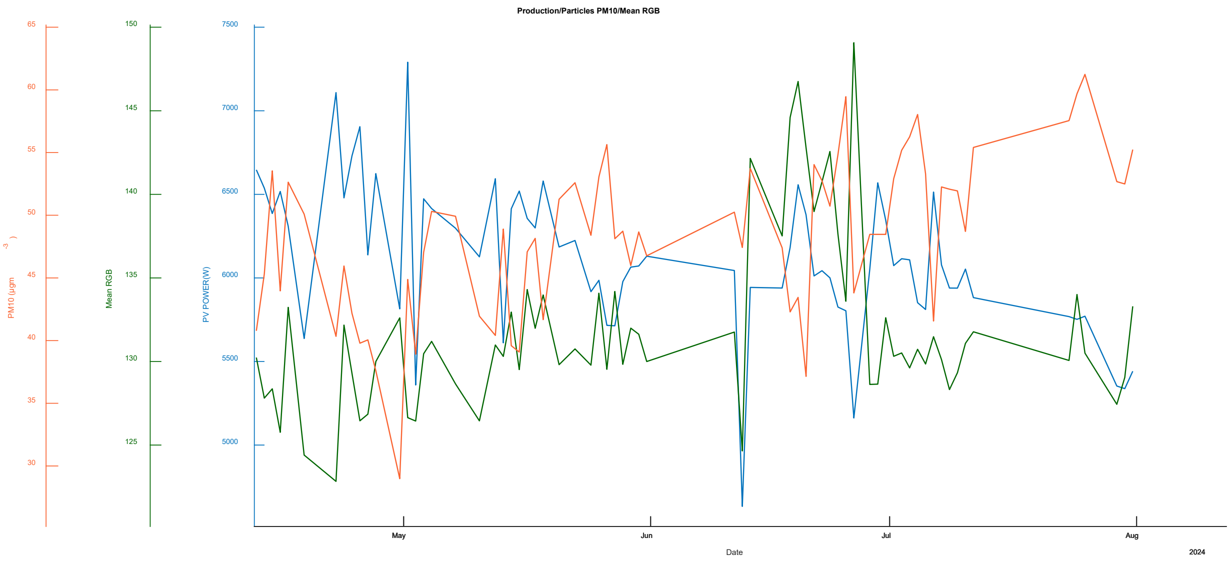

Figure 8. *Temporal Evolution of PV Power, RGB mean and PM10 (lateral vision)*

Analyzing the above graph, the average RGB channel follows the trend of PV production difficulties quite well. It can be determined, therefore, that this camera has a better representativeness of the PV solar field production. However, there are episodes that are not perfectly represented, such as some cases in May, where the production drops and the channel average rises. For these situations and being able to consider the presence of clouds on the horizon (they do not decrease the global irradiance below 850 Wm^{-2}), the diffuse component of the solar radiation has been included, to really see if there is solar scattering or not. Figure 9 represents the diffuse component measured in the horizontal plane, together with the PV production and PM10 production values.

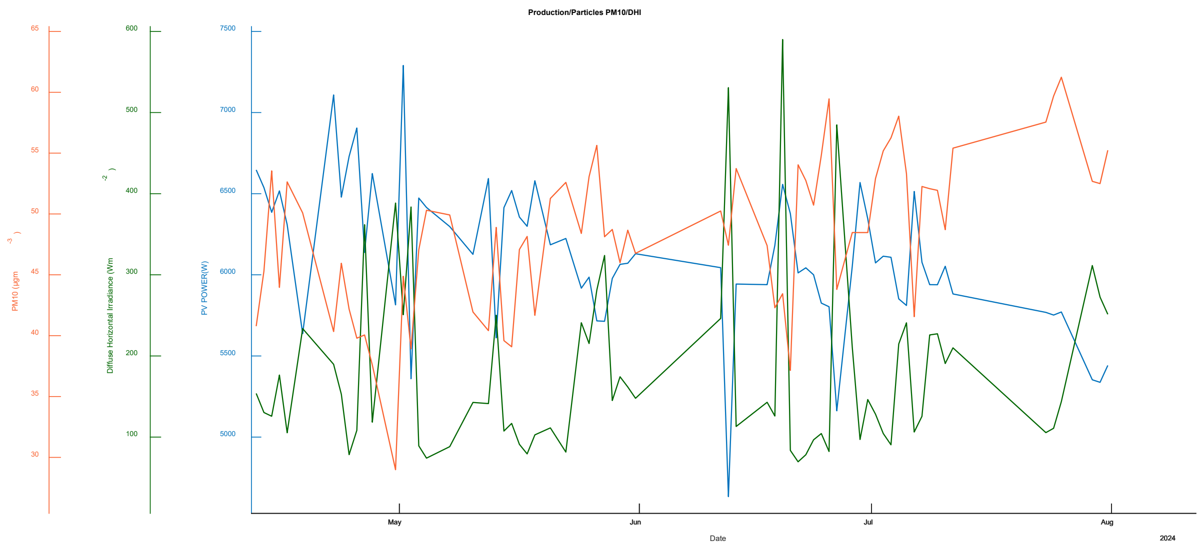

Figure 9. *Temporal Evolution of PV Power, Diffuse Horizontal Irradiance and PM10*

This graph confirms something that was commented previously. There are times when the diffuse component is high (above 100-200 Wm^{-2}) without having evidence of a dust episode (there are no high values or significant increases of particulate matter). This caused the production to go up while the RGB levels go down. Now it has been shown which phenomenon is behind these episodes and, for this, it will be necessary to consider diffuse irradiance in the studies.

4. Outlook and Conclusions

In this study, a novel approach for soil monitoring in photovoltaic plants has been presented using digital cameras and the analysis of RGB values, combined with radiation data and suspended particle measurements. The results obtained demonstrate that the average RGB values captured by strategically located cameras can act as reliable indicators of dirt accumulation on solar panels, showing a good correlation with radiation losses and energy production.

The integration of radiation and suspended particle data has allowed a better understanding of the factors that contribute to dirt accumulation and its impact on energy production.

In future works, the RGB images will be related to other environmental variables to see the correlation with them and compare with soiling rates from experimental PV plant.

In conclusion, the use of digital cameras and the analysis of RGB values, in combination with radiation and suspended particle data, constitutes an effective solution to address the challenges posed by dirt in photovoltaic plants.

Author contributions

Joaquín Alonso-Montesinos: conceptualization, methodology, visualization; writing -original draft preparation, writing -review and editing, supervision; **Enrique García-Campos**: methodology, resources, writing -original draft preparation, writing -review and editing; **Andrés García-Rodríguez**: conceptualization, methodology, visualization, writing -original draft preparation; **Verónica Abad-Alcaraz**: methodology, visualization, resources, writing -original draft preparation, writing -review and editing; **M. Mar Castilla**: conceptualization, methodology, supervision, project administration; **Manuel Pérez**: conceptualization, visualization, writing -original draft preparation, supervision; **José Antonio Carballo**: methdology, writing -original draft preparation, supervision; **Domingo Álvarez-Hervás:** conceptualization, methodology, visualization, resources, writing -original draft preparation, supervision, project administration.

Competing interest

The authors declare that they have no competing interests

Data availability statement

Data will be made available on request.

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