Machine Learning in Renewable Energy Application: Intelligence System for Solar Panel Cleaning

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Abstract: - The objective of this study is to develop an automatic cleaning system for Photovoltaic (PV) solar panels using machine learning algorithms. The experiment includes two phases. Phase one is to perform testing and reading of the sensor in 4 different classes which include no-dust, little dust, dusty, and very dusty during day and night time. The reading was taken using a visual inspection of the solar panel and the sensor reading using a multimeter. Phase two uses supervised learning to test and calibrate the sensor using the KNN algorithm. The classification was done using the data gathered from the sensor with one of the main classes identified. A total of 800 readings were taken. The results show the sensor reading taken during the night was more stable and accurate due to the sensor's sensitivity to noise which includes: heat and light during the daytime. Secondly, using machine learning (KNN algorithm) we get a 95% (with K=5) correct classification for the four main classes which determines the level of cleaning needed for the solar panel.

Key-Words: - Solar panel cleaning using machine learning, Machine learning in renewable energy application, classification for dust detection, sensor-based dust detection, Machine Learning, Classification Algorithms

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1 Introduction

We anticipate that governments worldwide will soon be compelled to provide alternative energy sources to maintain their economies or resort to programmed blackouts. A proposed solution to address this pressing energy crisis is the establishment of national energy centres across the globe. Jordan has followed suit with the formation of its own National Energy Research Centre in Amman. This centre aims to conduct research, development, and training in the fields of new and renewable energy while improving energy efficiency across various economic sectors, [1], [2]. Similarly, Algeria has implemented an ambitious program to promote the use of renewable natural resources. It has shifted towards alternative energy sources, which have become a rational and strategic choice due to the nature and cost of these resources. Notably, the research project highlights that Jordan's progress in this field is ahead of many other countries, with several universities following the Al-Zaytoonah University project, which has reduced electricity costs by 30%.

The implementation of this resource, particularly in steppe regions beyond the reach of rural electrification networks, has played a significant role in settling numerous nomadic families in proximity to their agricultural lands or grazing pastures. As a result, the demand for this type of solar energy equipment continues to surge in highland and steppe areas, as demonstrated in Figure 1.

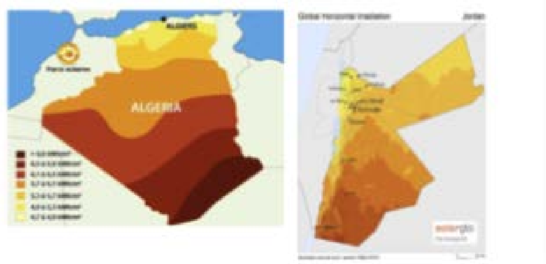

Fig. 1: Irradiation map in Algeria and Jordan

Algeria has an abundant solar field that can help the country transition from using disproportionate amounts of fossil fuels to clean energy. Despite having a significant energy potential exceeding 5 billion Gwh annually, its reliance on non-renewable energy sources still surpasses its solar resources. The country experiences an average of 2,250 hours of sunshine in the north and 3,600 hours (about 5 months) in the south, with respective potentials of 1,700 and 2,650 kWh per year, [10]. However, PV panels encounter various challenges that lead to energy losses. PV panels which are:

1. Partial shading: the environment of a photovoltaic module can include trees, mountains, walls, buildings, etc. It can cause shadowing on the module which directly affects the energy collected, [8].
2. Total shading: (dust or dirt) their deposit causes a reduction in the current and voltage produced by the photovoltaic generator (3-6%), [14].
3. Nominal power dissipation: the photovoltaic modules resulting from the industrial manufacturing process are not all identical. Manufacturers guarantee lower deviations of 3% to 10% around the nominal power. In practice, the photovoltaic solar module operates according to the performance of the worst panel: the nominal power is therefore generally lower than that prescribed by the manufacturer, [16].
4. Loss of connections: the connection between slightly different power modules causes slightly reduced power operation. They increase with the number of modules in series and parallel (3%).
5. Angular or spectral losses: the photovoltaic modules are spectrally selective; the variation of the solar spectrum affects the current generated by them. Angular losses increase with the angle of incidence, [18].
6. Losses by Ohmic drops: hmic drops are characterized by voltage drops due to the passage of current in a conductor of given material and section. These losses can be minimized with proper sizing of these parameters, [6].
7. Losses due to heat: the modules lose on average 0.4% of production per degree higher than the standard temperature (25 ° C under standard conditions of STC measurements). The operating temperature of the modules depends on the incident solar irradiation, the ambient temperature, the material colour, and the wind speed (5% to 14%), [11].
8. Losses due to the DC / AC performance of the inverter can be characterized by a yield curve as a function of the operating power (6%), [5].
9. Losses by tracking the maximum power point the inverter has an electronic device that calculates in real-time the maximum power operating point (3%), [3].
10. Losses due to the natural aging of the modules on average, a module in the open air loses less than 1% of its capacity per year, [9].

1.1 Problem of Dust on Solar Panels

The sunny deserts are an attractive option for solar energy, but the high level of dust presents a significant problem (Figure 2). To maintain optimal conditions, solar panel owners need a way to clean the panels regularly. If left uncleaned, the panels can lose up to 0.4-0.8% efficiency per day and up to 60% after dust storms. However, watering the panels with water in arid zones can be challenging and labour-intensive, particularly in remote desert locations with extreme temperatures that can reach over 122 degrees Fahrenheit during the day. Despite this, photovoltaic modules generally do not require much maintenance.

Fig. 2: Dust of solar panels

The first innovation is the development of automatic cleaning systems that use specialized robots to clean solar panels. These systems can be programmed to clean the panels regularly, reducing the need for human intervention in remote desert locations. The second innovation is the use of anti-reflective coatings on the surface of the solar panels, which can reduce the build-up of dust and improve their overall efficiency. These coatings are designed to repel dust and other particles, making it easier for wind and rain to remove them. With these innovations, the maintenance of large solar installations in desert environments can be made more efficient, safer, and less costly. Two recent innovations can contribute to the maintenance of large installations with greater safety for the personnel and less risk of damaging the modules:

a. Robot cleaners (remotely controlled by Wi-Fi) can clean the panels, [13];
b. Anomaly monitoring drones,

Advanced technologies such as drones equipped with high-resolution gyro-stabilized infrared cameras are being used in France for centralized tele-monitoring of solar installations. EDF ENR Solaire, a subsidiary of EDF Energies Nouvelles, created a solar roof control center in 2009 that now monitors 550 installations with a total power of about 55 MW, including 150 owned by EDF EN.

The drones enable remote operators to detect circuit faults at an earlier stage and intervene quickly and efficiently. Although drones have limited autonomy and are expensive to operate, their maneuverability and speed of intervention make them economically feasible.

Ensuring proper maintenance of a solar installation is crucial to maintaining its efficiency and preventing any loss in production, [17]. Even minor issues such as bird droppings or a thin layer of dust can significantly affect the output of the plant, leading to a decrease in income. In cases where micro-inverters or optimizers are installed, only the dirty panels will experience production loss, whereas a conventional photovoltaic inverter can impact the entire installation's production, [4]. To address this, various traditional and advanced cleaning methods are available, as depicted in Figure 3. Regular cleaning can help maintain optimal conditions for solar panels, thus ensuring maximum efficiency and income generation [20], [21].

Fig. 3: Traditional and advanced methods of cleaning the solar panels

2 Related Literatures

The significance of solar energy as a renewable energy source is progressively growing. However, dust accumulation on solar panels can significantly reduce their efficiency and output power. Regular cleaning is essential to maintain the performance of the solar panels. Various cleaning methods have been proposed, including manual cleaning, water sprinkling, and robotic cleaning. However, determining the frequency and extent of cleaning required can be a challenging task, [7].

Recently, machine learning techniques have been used to aid in the detection and classification of dust on solar panels. The KNN algorithm has been used to classify data into different categories, ranging from no dust to very dusty. This method is effective in determining the level of cleaning required for solar panels, [12].

Other machine learning algorithms, such as neural networks and decision trees, have also been applied to the problem of solar panel cleaning. For example, a decision tree-based approach was used to determine the optimal cleaning frequency based on weather conditions and dust accumulation, [25].

Robotic systems have been developed that use machine learning algorithms to detect and clean dust on solar panels automatically. These systems use sensors and cameras to detect dust on the panels and apply cleaning solutions using spray nozzles or brushes. Machine learning algorithms are used to enhance the cleaning process and ensure that the panels are cleaned taking into consideration efficiency and effectiveness, [15].

Overall, the use of machine learning for solar panel cleaning systems shows promise in improving the efficiency and reliability of solar energy production. Further research is needed to develop more accurate and efficient algorithms for detecting and cleaning dust on solar panels, [26].

3 Proposed Solution

Solar panels are exposed to various sources of pollution and fouling in their environment, such as industrial pollutants, car pollution, rain, acid, chimneys, pollens, dust, sands, leaves of trees, moss, mushrooms, salts in a marine environment, limestone, and residues of cleaning products, [19]. These pollutants not only lower the yield of the panels but also generate intense heating phenomena through the "hot spot" effect, leading to premature wear of the modules. Additionally, the angle of inclination of PV modules can also lower their efficiency. To address these issues, an electrical system consisting of a dust sensor, an Arduino Uno M-controller, two end races to designate the panel edges, a circuit L298D acting as a bridge to power the engine, and a DC motor for the translatory movement of ballet was simulated under Proteus. The results were promising, as shown in Figure 4.

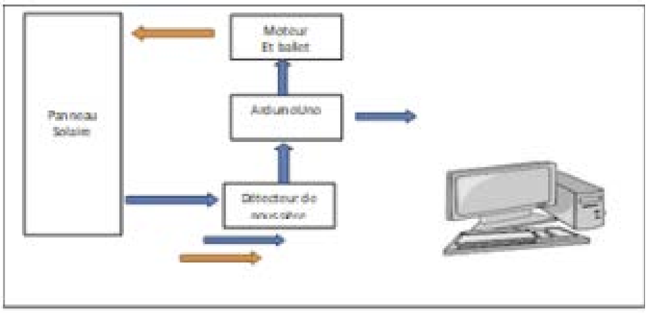
Fig. 4: Overall system layout.

A graphical user interface (GUI) allows for interactive control of an application using a mouse, as opposed to relying solely on keyboard commands. GUIs typically feature menus, buttons, scroll bars, checkboxes, lists, and text boxes, as depicted in Figure 5.

The creation of graphical interfaces in MATLAB has been made possible since version 5.0 (1997) with the introduction of a dedicated tool called GUIDE (Graphical User Interface Development Environment). With GUIDE, programmers can easily create intuitive graphical user interfaces using tools such as menus, buttons, elevators, checkboxes, checklists, and text boxes. The tool can be launched by clicking on the icon or typing "guide" in the MATLAB Command Window.

To connect the M-Controller to the PC, the "Connect" button is used, which turns green to indicate a successful connection. Clicking on the "START" button enables visualization of the system's state, and the sensor's value and engine status are displayed. When artificial dust is deposited on the sensor, the value of the sensor increases, triggering the engine to start the cleaning procedure of the PV panel.

The dust sensor comprises a transmitter and an IR receiver that continuously emit spokes until obstructed by dust, leading to a decrease in the sensor value. Figure 6 shows the quantity of dust on the sensor based on the sensor value. The proposed dust sensor has four classification categories: no dust, little dust, dusty, and very dusty.

Using the proposed sensor design, we use machine learning algorithms to classify the level of cleanliness based on the reading of the sensor and categories the level of cleanliness needed into 4 categories (refer to section 4).

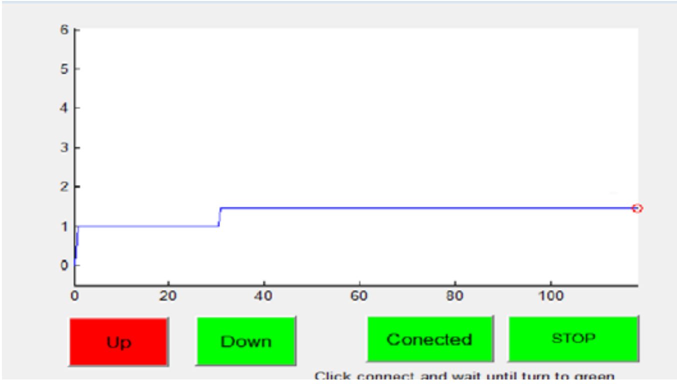

Fig. 5: Overall system layout

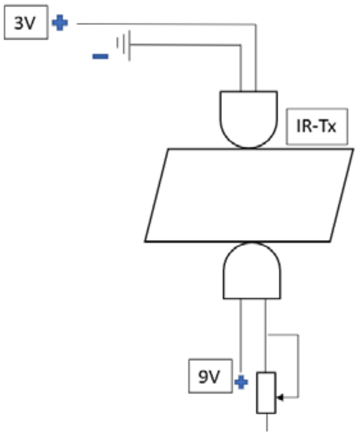

Fig. 6: Designed Dust Sensor

4 Machine learning for Dust Classification

Machine learning has emerged as a promising approach to automate the cleaning of solar panels. By leveraging sensors, image processing techniques, and machine learning algorithms, these systems can detect and classify the level of dirt and debris on solar panels and automatically clean them. Machine learning-based cleaning systems have the potential to significantly reduce the cost and time required for solar panel maintenance and increase the efficiency and lifespan of solar energy systems. In this context, research on the development of machine learning-based solar panel cleaning systems has gained significant attention in recent years, [23], [24].

Machine learning has been used in a variety of applications such as data mining, optimization, and classification, [22]. In this section, we use machine learning to classify the level of cleaning needed for the solar panel. Our approach starts with measuring sensor sensitivity to multiple factors which include noise, heat, and light. The experiment includes taking the sensor reading for (no-dust) surface using a multimeter, where first the surface will be cleaned and then the reading is taken. this approach was applied to data gathering during the night and daytime. A total of 800 reading was taken using a multimeter and visual inspection of the solar surface for the dust. The results show that the sensor failed to detect (no dust) during daylight as the reading was fluctuating and unstable using a multimeter as shown in Figure 7 whereas, during the night the results show that the multimeter reading shows stability as shown in Table 1, where during the night-time the average reading was 0.84 volts with stander deviation 0.3, whereas during the daytime the average was 0.66 with stander deviation 0.15.

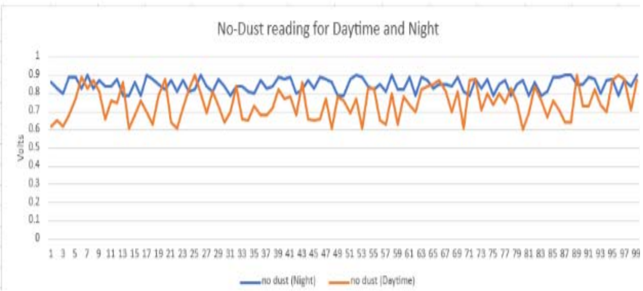

Fig. 7: Sample of Dust level and multimeter reading for No-dust class

Table 1. Average reading in volts during Daytime and Night time

Time period	Average reading	Standard deviation
Night	0.84	0.3
Day	0.66	0.15

Figure 8, shows a small sample of the multimeter reading for each class during daytime. As shown noise, heat, and light will affect the reading of the sensor and the decision-making process for determining cleaning level. Using the KNN algorithm we train a classifier to identify the four different types of classes where we gain a 56% on average, this indicated that the classifier has above the chance to correctly classify each class.

Figure 9 shows a small sample for the multimeter reading for each class during night-time, where the reading shows stability and consistency for the voltage reading for the no dust class. As daytime data was insufficient, we start gathering sensor readings during the night for identifying four types of classes which include no-dust, little dust, dusty, and very dusty. These classes were introduced to classify the sensor reading and identify the level of cleaning needed. A total of 400 reading was gathered for the four types of classes and used the KNN algorithm to classify and cluster the data gathered. Using the KNN classifier we get 95% accuracy, where we found the best K value is (5) using Euclidean distance and cross-validation criteria on the data. We use supervised learning by labeling the data and training the KNN classifier. Table 2 shows the KNN classifier and the detection rate for each class.

Figure 10 shows the cluster for each class after the classification is done, as shown each class has its cluster were using the KNN algorithm we can classify each sensor reading and determine the level of cleaning needed.

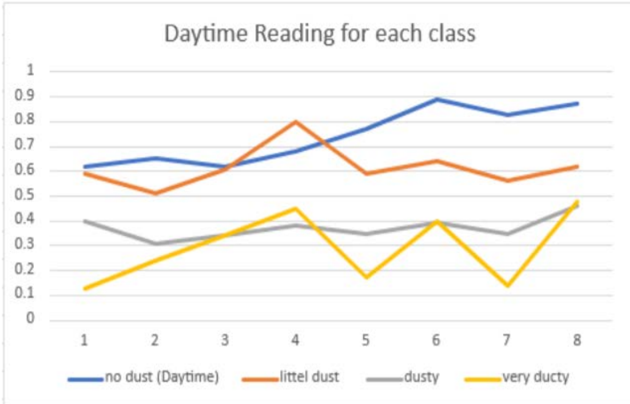

Fig. 8: Sample for the reading for each class during Daytime

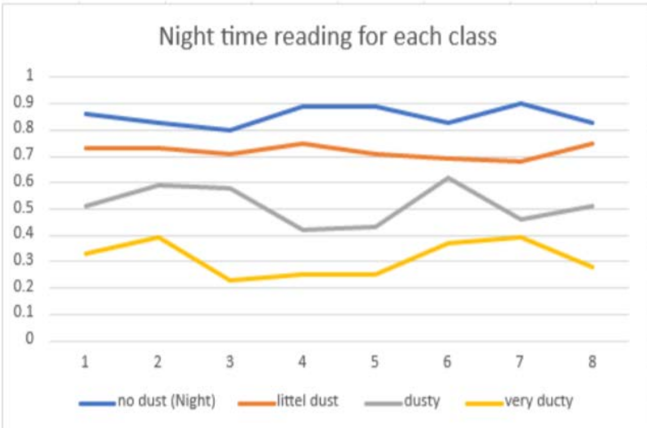

Fig. 9: Sample for the reading for each class during nighttime

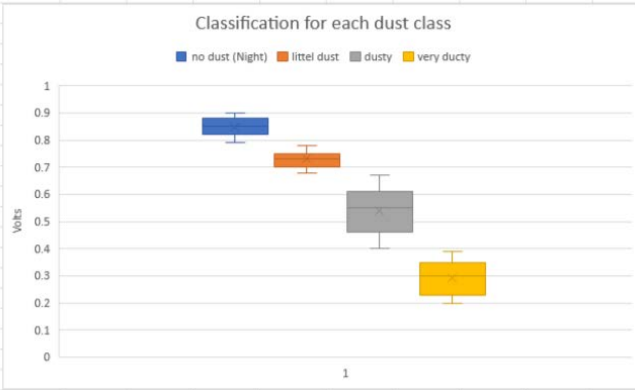

Fig. 10: Classification for each dust class

Table 2. KNN classifier accuracy %

Classes	K = 1	K=2	K=3	K=4	K =5
No-dust	0.50	0.52	0.60	0.80	0.94
Litte dust	0.56	0.57	0.65	0.82	0.96
dusty	0.48	0.51	0.70	0.85	0.97
very dusty	0.6	0.58	0.72	0.87	0.93

5 Conclusions

In this study, the impact of dust on solar panels is examined by measuring various voltages at different times of the day. Using machine learning techniques to utilise and determine the level of cleaning required for the solar panel a total of 800 readings were gathered. Using the KNN algorithm to classify the data into four categories: no dust, little dust, dusty, and very dusty. The results show that sensor readings are consistent during night-time but unstable during daylight hours due to multiple factors such as heat, noise, and light. By employing the KNN classifier, the daytime data achieves 56% correct classification. On the other hand, the KNN algorithm applied to the night-time data demonstrates a 95% correct classification with a value of K=5.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

-Ali Al-Dahoud and Mohamed Fezari collaborated to design and develop a sensor capable of accurately measuring the voltage of both clean and dirty solar panels, as described in section 3.

-Ahmad Al-Dahoud, applied a machine learning algorithm to analyse the collected data, as outlined in section 4.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflict of interest to declare.