



Solar Tracking System Using pixel identification algorithm

Nader Behdad^{*1}, Sunil Kumar²

¹Electrical and Computer Engineering , The Polytechnic University of the Philippines,
Manila, 1016, Philippines

²School of Computer Science, University of Petroleum and Energy Studies,
Dehradun, 248001, India

Emails: ohowpy@gmail.com; skumar@ddn.upes.ac.in

Abstract

On cloudy days, an intelligent technique to optimizing the direction of continuous sun tracking devices is proposed in this research. When it comes to weather, direct sunlight is more essential than diffuse radiation in a clear sky. As a result, the panel is always pointing towards the sun. When the sky is overcast, the solar beam is near to zero, and the panel is positioned horizontally to receive the most dispersed radiation. Under partially covered conditions, the panel must be aimed at the source emitting the most solar energy, which can be located anywhere in the sky dome. Thus, the idea behind our technique is to analyze images taken by a ground-based sky camera system in order to identify the zone in the sky dome that is thought to be the best source of energy under foggy situations. The proposed method is put into practice utilizing an experimental setup built at Mansoura city in north Egypt. The findings were quite good under overcast situations, and the intelligent technique gave efficiency gains of up to 9% compared to typical continuous sun tracking systems.

Keywords: Clouds detection; Deep learning; Photovoltaic; Sun tracker;

1. Introduction

Artificial intelligence (AI)-powered optimization applications have been rapidly spreading across a wide range of industries in recent years. Optimization algorithms help in the medical field with things like treatment planning, resource allocation, and patient scheduling [1-2]. Production, distribution, and pricing strategies can all be optimized with the help of economic optimization methods, leading to better market results and more profits [3-4]. The goal of renewable energy optimization is to create more environmentally friendly and long-lasting electrical grids by maximizing renewable energy generation and storage [5-7]. Artificial intelligence (AI) is being used to optimize solar cells, which improves their design and efficiency and hence their ability to convert sunlight into usable energy. To enhance antenna design and performance for improved signal reception and transmission in communication systems, AI algorithms are used in antenna optimization [8]. Optimization algorithms have been shown to improve patient outcomes and decrease healthcare expenses by aiding in areas such as patient monitoring, disease diagnosis, and personalized treatment recommendations [9]. Optimization and AI's complementary nature has broad application, fostering new developments and better results in many fields [10].

The worldwide shortage of energy has prompted numerous researchers and renewable energy sources are receiving increased attention from engineers [11]. These results prompted scientists to look at alternative strategies and materials [12] for transforming solar energy into usable forms of power. Photovoltaic (PV) systems are used to transform the energy from the sun into electricity. The high cost of installing solar systems is a major barrier to their widespread use. More and less expensive versions of these systems have been the subject of extensive research. Artificial intelligence (AI)

algorithms have been shown to significantly affect PV system performance [13]. Modelling, sizing, controlling, diagnosing faults, and estimating production are all possible in solar systems with the help of AI algorithms. For each application category, it contrasts AI algorithms with their classical counterparts.

The use of AI in solar panels is seen in Figure 1 [14-21].

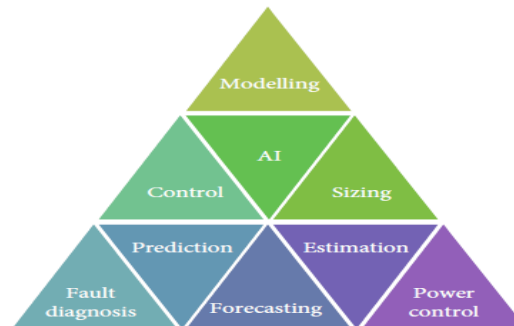


Figure 1: AI applications in solar panel

The slicing process is the work of breaking down the predictions made in the past. With this information, the deep learning algorithm could more accurately forecast the output features needed to build the solar panel outputs. Modules for tracking the sun and managing energy are controlled by the control unit. Figure 2 is a simplified diagram of the many different uses for PV systems, which rely heavily on precise modelling of solar cells.



Figure 2: Photovoltaic applications

The parameters of a PV system must be determined numerically before the system can be modelled. Both the single-diode and double-diode solar cell circuits have the same efficiency [22]. Saturation current, series resistance, shunt resistance, and photogenerated current are the five characteristics of the single-diode model, each of which is represented by a single value [23]. The double-diode model relies on seven inputs. Accurate estimations of these characteristics are crucial for the modelling and sizing of PV systems. Several published standard approaches for calculating solar cell properties are readily available online [24].

Above, [25] describes an analytic-numerical method for the five-parameter single-diode model. The analytic portion is used initially as a springboard for developing the numerical solution. The article [26] describes a pattern search strategy that can be applied to single diodes, two-dimensional diodes,

and photovoltaic modules. However, conventional approaches cannot reliably foretell the characteristics of solar-electricity producing modules. As a result, many researchers have begun using AI tools for parameter discovery [27-32]. Extremely potent computational systems can be constructed by the integration of AI with other technologies. One common thread across the many alternative methods is an effort to compensate for shortcomings in more conventional approaches. The purpose of computer system design is to create systems that perform better, consume less energy, and accomplish more. To accomplish this, you may need to learn quickly and extrapolate from what you already know. Implementing the appropriate mix of smart technologies can. Additionally, several developed nations have implemented sector-specific methods to promote the utilization of sustainable supplies. Photovoltaic (PV) technology is one example of a promising renewable energy (RE) technology. With the help of AI and other technologies, we can create supercomputers with unfathomable processing capability.

The output of a unit can be determined by summing all of its values. Predictions regarding past performance from deep learning are useful for adjusting course in lagging areas. Improving the energy output of solar panels is the primary result of this work. A sophisticated deep learning approach based on AI is used to make these enhancement predictions. Thus, the generation of energy and its administration are carried out in an artificial manner. The proposed model's findings were improving to create practical systems that outperform those created with more conventional methods.

2. Related Work

A neural network (ANN) is a system of many tiny processors working together. These parts play crucial roles in the transmission of data. An incoming connection's data can have an input and a weight applied to it. By summing all of the values, the output of a unit may be determined. Despite being implemented in computational form, ANNs do not have assigned tasks. Machine learning algorithms are not explicitly taught to recognize patterns; rather, they are trained to do so by humans. After being trained, they can be asked to predict or classify brand-new patterns. Computer programs, physical models, and even functioning systems can all be used to educate artificial neural networks [33-38].

Using an ANN to process numerous inputs and generate usable outcomes is a practical option, especially for designers who need to work with enormous datasets. Building artificial neural networks calls for a deep familiarity of the workings of the human brain and nervous system. To create a black box model of a system, processing units must be linked together with varying link weights. Modelling. Between the input and the output, there may be additional layers. In order to obtain a result in all hidden and output neurons [39-44], a nonlinear transfer function is used to process the sum of the weights of each input and output.

A neural network can analyze large amounts of data with little to no guidance from an external rule set, and it can do so even when given skewed or otherwise erroneous input. Traditional symbolic or logic-based approaches have failed to address these capacities [45-48]. Soon, traditional computers and AI methods will understand that neural computing can be utilized as an alternative or supplement. Once the network is trained, neural computing may offer a substantial speedup over traditional computing. The ability of a system to be trained with data sets rather than with code could be more time and money efficient when making adjustments. To learn more about the system, ANN uses adjusting the weights that connect nodes. Pattern matching and data reduction are only two of the many applications for artificial neural networks (ANNs). Artificial neural networks (ANNs) are a popular technique for forecasting and prediction because they are a promising and rising technology [49-50].

Neural networks can be made more effective by including fuzzy approaches. Allowing a neural network to interpret ambiguous information could be one answer. Another approach [51] that has been proposed is to add some fuzzy characteristics to the input data before passing it on to the fuzzy neural processor. Every network node has the potential to contain modified neurons, which can transform murky input into sharp output. The input vector includes fuzzy values for the weights that link the node to the nodes in the layer below it, as well as the weights that link the node to the nodes in the layer below that. The input data and the weights presented by the membership functions are defined as follows: the computation requires two membership functions, one of which represents the original weighted integration and the other of which reflects the weight of the fuzzy inputs via an updated

summation method. By performing a centered operation on the result and comparing the results, a crisp value can be used to determine the node's output [52-53].

The total energy generation from solar panels is significantly affected by their direction due to the ever-shifting location of the sun. Solar collector efficiency can be improved in two major methods. Collectors are either permanently installed or have a movable tilt that is changed on a monthly or seasonal basis in the first method [54]. Using a single or multiple axis tracking mechanism, they can be consistently aimed at the sun [55]. The dual axis tracker is the most effective method of propulsion since it enhances solar radiation capture by around 30% compared to the fixed mount and by 6% compared to the tilted array. A tracker that only follows one axis [56].

When taking into account atmospheric circumstances, the majority of the world's solar energy [57] that reaches Earth originates from the sun, and the rest comes from diffuse solar energy in clear sky conditions. Diffuse radiation, however, is amplified by atmospheric factors like clouds and pollution. So, in cloudy weather, when the sun can't be tracked, the horizontal position becomes the best option for capturing the isotropically-distributed radiation from the entire sky [58]. Diffuse radiations in a partly cloudy sky are distributed anisotropically, with certain areas of the sky reflecting more energy than others due to differences in cloud location and movement.

Major considerations in assessing and forecasting solar irradiance [59] are cloud distribution and characteristics, which are most commonly studied using satellite pictures. However, satellite pictures' limited spatial and temporal resolution is insufficient to meet the demands of solar energy system control. To compensate for the limitations of satellite cloud observations in terms of geographical and temporal resolutions [60], researchers have begun to examine photos taken by ground-based sky camera systems.

There have been several attempts to create detection algorithms that distinguish cloud-representing pixels from sky-representing background pixels. They are, in fact, segmentation methods that identify pixels based on conditional criteria derived from the relative strengths of the blue B and red R components of the RGB pictures. Using one or two thresholds applied to the R/B ratio for the total sky images WSI [61], some researchers have separated the sky into three classes: opaque cloud, thin cloud, and clear sky. The pixel example is established in other publications by looking at the difference between R and B [62]. To combine the latter two methods, a hybrid thresholding technique [63] converts color images to normalized R/B ratio images (NRBR) before applying a thresholding algorithm to find cloudy areas within the transformed images. However, most cloud classification algorithms have trouble with large uncertainty ranges for near-horizon and circumsolar cloud detection. We present a new cloud identification approach based on fuzzy inference systems (FIS) to address this issue.

Our first goal was to suggest a clever way to use fuzzy logic to identify instances of sky in photos taken from the ground. The second objective is to extrapolate the previous part's findings so that the solar panels are oriented in such a way as to receive the most possible solar energy from the sky. When there is a clear sky overhead, the solar panel can be angled such that it receives the most direct sunlight possible. The following is the structure of this paper:

In Section 3, the experimental setup is described. In Section 4, we introduce the intelligent orienting technique. In section 5, we show results. In Section 6, we present a conclusion and directions for future study.

3. Experimental Setup

An experimental setting designed by researchers at Mansoura City (Latitude = 31.0167 N, Longitude= 31.5 E) has been used to test the intelligent technique described in this study. The system consists of the following components: two SM34SPM dual-axis sun trackers, a microcontroller board, and two SUNSET-PX 60E polycrystalline photovoltaic panels. Both are positioned properly with respect to the sky, but one follows the sun around continually. A computer equipped with an NI-USB-6008 data acquisition card. Cameras pointed at the sky from the ground. A ground-based 5-megapixel color CMOS sky camera was utilized to capture the photos for this research. At a rate of once every 20 seconds, 1920 x 2560 images at 8 bits per channel are gathered. Since 2020, all photos have been kept in a database in the form of HDF5 files, which use a hierarchical structure to hold data and metadata. The HDF 5 files also include meteorological measurements such as solar irradiation and atmospheric

turbidity factor in addition to the photographs acquired. We were able to account for all possible sky circumstances in our experiments thanks to the large quantity of saved photos.

Specifically, the algorithm finds the location on the sky dome that emits the most solar energy during the period t (fixed in this study at $\Delta t = 15$ minutes), calculates the zenith and azimuth angles of the last point, and then sends them via RS232 serial communication to the microcontroller in the tracker.

4. Image based orientation method

Several stages make up the suggested procedure, as shown in the flowchart in figure 3. First, the image taken at time t is analyzed for evidence of a cloudy sky. The solar panel will follow the sun during clear weather, but if clouds are present, it will switch to a horizontal orientation. If the sky is only partially clear, the solar panel should face the geometrical center of the brightest section of the image $I(t)$. At each iteration, called t , the position is revised to reflect the new procedure.

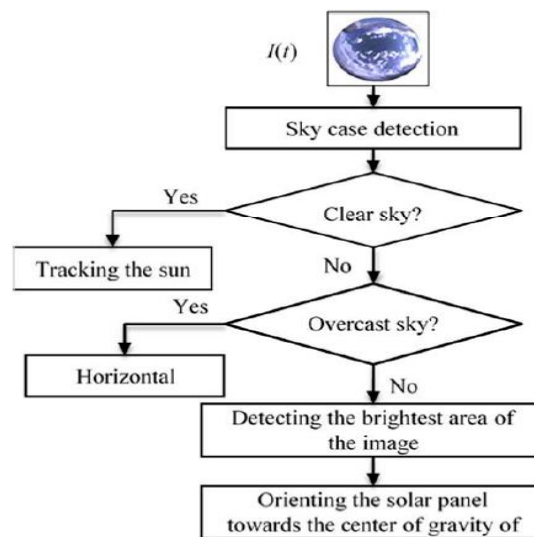


Figure 3: Block diagram of intelligent sun tracking method

In our scenario, we use meteorological factors as well as human views and values, both of which call for the incorporation of qualitative data and human expertise into the modelling process, which is where fuzzy inference systems (FIS) systems come in. The Mamdani-type and the Sugeno-type are the two primary architectures of fuzzy inference systems. It is assumed that the membership functions generated by Mamdani's fuzzy inference approach [64] will be fuzzy sets. Systems of the Sugeno type can be modelled, provided the membership functions at the system's output are linear or constant [65]. For example, in this case a Sugeno-type, An inference algorithm sorts the pixels into clear, partly cloudy, and overcast regions.

circumsolar pixels based on the normalized values of each pixel's red, green, and blue components. Fuzzification, a fuzzy rules base, and defuzzification are the three key steps in creating a fuzzy inference system. The goal of the fuzzification process is to use fuzzy subsets to convert the discrete values of input and output variables to the interval $[0,1]$. In this setting, the possible values for each variable are broken down into categories denoted by words like "small," "big," "high," etc.

Fuzzy membership functions, such as the triangle, sigmoid, trapezoidal, Gaussian, or singleton, can be used to characterize the most recent linguistic ratings [66]. The quality of the user experience is crucial when deciding which membership functions to utilize [67]. For clarity's sake, we employ triangular and trapezoidal fuzzy membership functions, as shown in figure 4. Each of the input variables is scaled from 0 to 1 and fuzzified into three membership functions labelled L ("low"), M ("medium"), and H ("high") in this diagram.

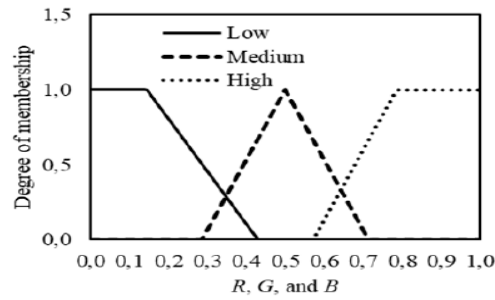


Figure 4: Fuzzification of input variables

We defined four constant membership functions in the output, one for clear sky, one for partially overcast, one for mostly cloudy, and one for very cloudy conditions. The following is the form that the fuzzy rules take A logical conclusion is that B is "H" if R is "L" and G is "L" and R is "L." Then, "clear sky pixel" describes this situation. The outputs of the several fuzzy rules are combined to produce a single membership function, which is then applied to the fuzzified inputs. Then, a defuzzification procedure is applied, which takes the muddled result and returns a clear number. In this study, we use a weighted average:

$$z_w = \frac{\sum_{i=1}^m \mu_A(z) \cdot z}{\sum_{i=1}^m \mu_A(z)} \tag{1}$$

where Z_w is the clean output, $A(z)$ are the combined membership functions, and z is the center point of the set. Once the pixel classes have been established, the percentage of cloud cover in the entire image can be used to identify whether or not the image features sky.

The pixels in a scene that make up an object are given a "brightness" attribute based on how much light they appear to be emitting or reflecting. Brightness, then, is a measure of how much light an object lets in. True color image I is grayscale I_g to find the brightest area, and then I_g is changed to binary image I_b by swapping out all the pixels. pixels in the input image with brightness over the threshold with the value 1 (white), and by switching out the values for all the other pixels with those from the threshold 0 (black).

5. Results

Our study here aims to improve the performance of continuous sun trackers in a variety of climates. Thus, the proposed method was assessed by contrasting the yearly energy production of a solar array using a classical continuous sun tracker with that of a solar array using an intelligent sun tracker. According to the data provided in figure 5, the intelligent tracker significantly improves the efficiency of the sun tracker, as the solar panel driven by it produces more energy than the one driven by the traditional tracker throughout the whole experimental time.

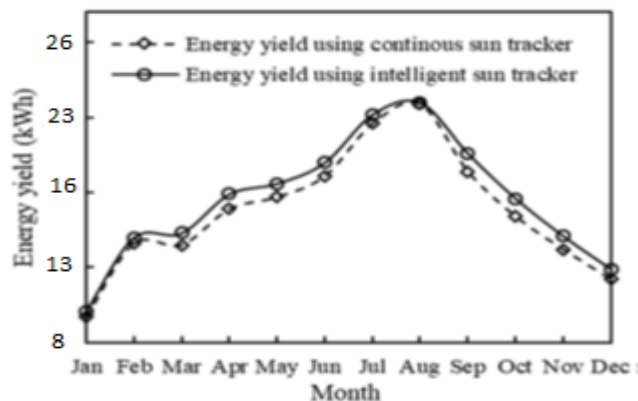


Figure 5: Energy yield of the solar panel using continuous and intelligent

sun trackers in 2022

To evaluate how well our method works in various climates, we calculate the monthly gain of energy (g) by using:

$$g = \frac{\sum(E_i - E_c)}{\sum E_i} \quad (2)$$

where E_i (kWh) is the power generated by the PV system using the intelligent orientation method, and E_c (kWh) is the power generated by the PV system using the traditional sun tracking method (continuous solar tracking systems).

Table 1 displays the findings. This table shows how the amount of time spent in the sun affects the amount of energy gained.

Table1: Sunshine and gain through 2022 year

Month	Sunshine Duration (h)	Gain (%)
January	120	7.8
February	195	7.8
March	210	7.7
April	247	7.8
May	262	6.6
June	292	6
July	340	3.3
August	398	0.5
September	301	7.7
October	210	9.5
November	138	8.9
December	115	8.9

When the gain is high and the last parameter is little. This is to be expected, as increased scattering by particulates in the atmosphere significantly reduces direct solar radiation and sunshine duration under partially clouded and cloudy skies, rendering sun tracking inefficient.

6. Conclusion

In this study, we present an intelligent sun tracking method for improving the performance of standard dual axis sun trackers in a variety of climates. The smart method relies heavily on fuzzy inference algorithms and the processing of sky photos. The sky is identified using a pixel identification method, and the size of the clouds is calculated based on the entire image. Cloud movement is estimated with the use of block matching algorithms (BMAs). Next, a fuzzy inference system is fed information about the cloud's size and movement speed in order to determine where exactly the PV panel should be installed. Our method was tested in an experimental setup, and the results, gathered over the course of a year, reveal that energy yield rises in direct correlation to cloud duration. Using the newly created algorithm in regions with different climates is the next logical step for this project.

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