Solar Radiation Forecast Using Cloud Velocity for Photovoltaic Systems

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Abstract. Today, solar energy is used in a many different ways. One of the most popular technological developments for this purpose is photovoltaic conversion to electricity. However, power fluctuations due to the variability of solar energy are one of the challenges faced by the implementation of photovoltaic systems. To overcome this problem, forecasting solar radiation data several minutes in advance is needed. In this research, a methodology to forecast solar radiation using cloud velocity and cloud moving angle is proposed. Generally, a red-to-blue ratio (RBR) color model and correlation analysis are used for obtaining the cloud velocity and moving angle. Artificial neural network (ANN) forecast models with different input combinations are established. This methodology requires lower computational time since it only uses part of the pixels in the sky image. Based on R-squared analysis, it can be concluded that the ANN model with inputs of cloud velocity and moving angle and average solar radiation showed the highest accuracy among other combinations of inputs. The R-squared value was 0.59 with only a relatively small sample size of 42. The proposed model showed a highest improvement of 75.79% when compared to the ANN model based on historical solar radiation data only.

Keywords: *cloud velocity; forecasting model; photovoltaic systems; sky image; solar energy.*

1 Introduction

The generation of energy via fossil fuel resources has led to global warming and climate change. This causes the overall temperature of the atmosphere to increase, negatively affecting not only the environment but also mankind. Therefore, renewable energy technologies have enormous potential. Renewable energy is defined as energy from a source that is naturally replenished after use, such as the wind or solar power.

Among all renewable energies, solar energy is unarguably the most popular choice for generating electricity because of its massive amount of supply compared to other renewable energy sources [1]. It is capable of powering cities

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and industries using large solar plants while at the same time offering stand-alone capability even in the most isolated rural regions.

Malaysia is located in the equatorial region and has a tropical rainforest climate. It receives higher solar radiation than most of the other countries in the world. Therefore, generation of electricity from solar energy in Malaysia has great potential when compared to other countries.

Solar energy can be harvested and transformed into useable electricity through the use of current solar energy technologies such as photovoltaic (PV) conversion. PV conversion works in such a way that electricity is created directly from the sun via solar panels. PV cells are mainly composed of silicon and other semiconductor materials [2]. These semiconductors can help to store surplus generated energy when solar radiation is abundant. PV systems are suitable for use in housing because there is absolutely no noise produced by PV panels as they convert sunlight directly into usable electricity.

In recent years, the usage of PV system has increased due to research and improvement in PV solar panel efficiency and the price of solar panels dropping continuously. This has given a significant boost to the performance of solar PV systems. However, the electricity output of a PV system in a specified future time period cannot be determined accurately because of the irregularity of solar radiation caused by various weather conditions (see Figure 1).

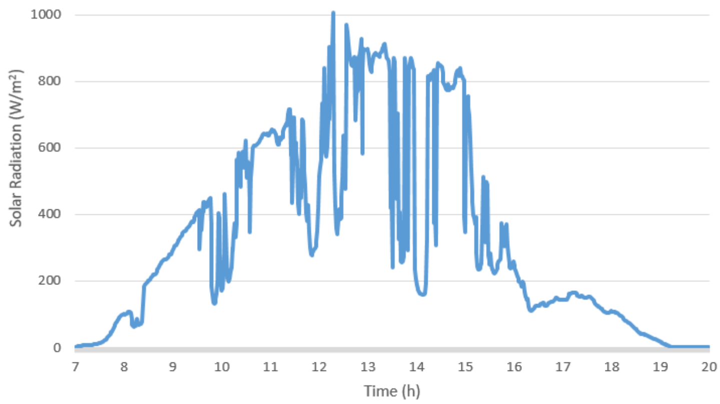

Figure 1 Measured solar radiation during daytime.

This is because the amount of solar radiation input is the most important parameter for the electricity output of a PV system [3]. For this reason, PV systems are considered uncontrollable power generators in utility networks, whose electricity output fluctuation impacts the stability of the power system

[4]. Therefore, accurate short-term solar radiation forecasting, i.e. several minutes in advance, is needed for power-demand management. Thus, the power output of the PV system can be forecasted in order to provide a stable and continuous electricity output [5].

To date, several methods for forecasting solar radiation have been proposed. Generally, there exist two different approaches in solar radiation forecasting, i.e. the meteorological data based approach, and the sky image based approach. Meteorological data based prediction methodologies use meteorological factors such as wind speed, atmosphere temperature, air humidity, sunshine duration etc. as inputs to predict solar radiation. Mellit [6] used a database of latitude, longitude, altitude, and daily global solar radiation collected from 60 meteorological stations in Algeria to develop a prediction model. A few years later, Mellit [7] developed an adaptive neuro-fuzzy inference scheme (ANFIS) model to predict daily total solar radiation data from 10 years of data of sunshine duration and ambient air temperature. Senkal [8] collected meteorological and geographical data, such as latitude, longitude, altitude, mean monthly diffuse radiation, and mean beam radiation, for the input of ANN, and used a period of 5 months to collect meteorological data from 12 cities spread over Turkey. Mousavi [9] developed a hybrid method coupling ANN and simulated annealing (SA) for the prediction of daily solar radiation using meteorological data such as minimum, maximum and average air temperature, relative humidity, atmospheric pressure, wind speed, and earth skin temperature collected in the city of Mashhad, Iran for developing the model. Xue [10] used 20 years of recorded solar radiation values and daily meteorological variables, including sunshine duration, mean temperature, rainfall, wind speed, relative humidity, daily global solar radiation, and daily diffuse solar radiation from Beijing, to optimize a back propagation neural network (BPNN) prediction model for solar radiation. Bakirei [11] used 15 years of data of bright sunshine hours and daily global solar radiation to derive correlations for forecasting daily solar radiation in the Eastern Anatolia Region (EAR) of Turkey. Although meteorological data can provide reasonably good prediction results, this approach is not economical due to the expensiveness of the equipment, the time taken for the establishment of the prediction model, and the difficulty of obtaining the meteorological data from weather stations.

On the other hand, the sky image based approach predicts solar radiation by using information extracted from sky images. It requires only a camera, which is easily accessible and low-cost when compared to the meteorological data based approach. Nevertheless, this approach relies heavily only the ability to extract useful and important information from images.

Various kinds of features can be studied from sky images, such as the area of a sky region [12] and the motion vector field of clouds [14]. Clouds have been found to be the major factor in the atmosphere system that affects the incoming solar energy [13-15]. In fact, the fluctuation of solar radiation is caused mainly by clouds. When sunlight is blocked by clouds, the clouds absorb and scatter the shortwave part of the radiation spectrum and absorb the long-wave part and re-emit it downwards and into space, thus decreasing the amount of solar radiation that hits the ground [13]. As such, most sky image based methods focus on the extraction of cloud information, e.g. optical thickness, cloud cover, cloud velocity, etc.

Among all the types of cloud information, cloud cover is the most essential factor that affects the amount of solar radiation [13]. For example, Alonso [16] processed sky images and combined them with radiometric data to identify the cloud cover in the sky. However, special equipment such as a pyrheliometer is needed to get the radiometric data required for the identification of the cloud cover [16]. Martínez-Chico [17] made a classification of types of cloud cover using the beam transmittance (ratio between direct radiation incidence on the surface and extraterrestrial solar radiation) and hemispeherical sky images. This method also requires the measurement of solar radiation. On the other hand, cloud velocity obtained from two consecutive sky images is deemed to be the easiest accessible method for the prediction of cloud displacement and hence the prediction of cloud cover [14,15].

To date, several researches have been done that studied cloud velocity [14,15]. Hammer [14] developed a statistical method to determine cloud velocity from satellite images in which the calculated motion vector fields are used to forecast solar radiation. Alonso-Montesinos [15] used a total sky camera to capture sky images for the calculation of cloud velocity, after which the cloud velocity was used to conduct solar irradiance forecasting. David Bernecker developed a method to forecast global horizontal irradiance up to a maximum forecasting time of 10 min. The forecast was further improved by using a dense vector field of cloud displacement vectors calculated by using a non-rigid registration algorithm [18]. Chow [19] developed a method for the estimation of sky cover, cloud shadow, and cloud motion vector, generated by cross-correlating two consecutive sky images. Thus, cloud locations up to 5 min ahead were forecasted.

Although their prediction results are reasonably good, most of these researches used the whole sky image, where every pixel is analyzed, resulting in high computational time. Owing to the fact that PV systems need to generate electricity continuously, a methodology capable of predicting solar radiation in advance is crucial. Thus, a methodology that predicts solar radiation using the cloud velocity is proposed here.

2 Methodology

Generally, the methodology can be divided into five phases. This is presented in the flow chart in Figure 2.

Figure 2 Flow chart of research methodology.

2.1 Data Collection

A GoPro camera (model HERO4 Silver) was mounted on a solar tracker and used to capture sky images at intervals of 1 minute. The solar tracker makes sure that the camera traces the sun and that image captured has the sun in middle. This is very important in determining the cloud movement direction in the sky image; the details will be discussed in Section 2.4. A coin was placed over the lens of camera to reduce glares caused by the sun (see Figure 3). For example, a set of sky images taken on the 27th September of 2016 is shown in Figure 3, each set consisting of two consecutive sky images at an interval of 1 minute. The solar radiation intensity data were also collected at the instance the sky images were taken.

(a) (b)

Figure 3 (a) and (b) Sky images at 11.32 am – 11.33 am.

2.2 RGB & RBR Extraction

Firstly, the direction of cloud movement is determined visually by comparing two consecutive sky images. Based on this direction, a line (AB) is drawn across the center of the cloud where its velocity is to be determined (see Figure 4). Depending on the size of the clouds, the length of the line AB is varied accordingly (see Figure 4).

(a) (b)

Figure 4 (a) and (b) Sky images at 11.32 am – 11.33 am with drawn line.

As shown in Figure 4, point A is the starting point of cloud movement and point B is the end point of cloud movement. After line AB is drawn, the RGB values of each pixel along the same line are extracted. The extracted RGB values are then used to calculate the RBR values, which stands for the red to blue ratio, which is represented by Eq. (1). The RBR values are used because they provide a clear distinction between clear sky and cloud coverage areas due to the fundamental difference in light wave scattering by clouds versus a clear sky [20].

$$RBR = \frac{R}{B} \tag{1}$$

where, R = amount of red in the RGB color model, B = amount of blue in the RGB color model.

2.3 Cloud Velocity Calculation

Once the RBR values for line AB in Image 1 and Image 2 have been obtained, the RBR values are used for a sequence of correlation analyses between the lines drawn on Image 1 and Image 2 to determine the number of pixels travelled by the cloud. That is, for the two consecutive images, the following correlation analysis is calculated in Figure 5.

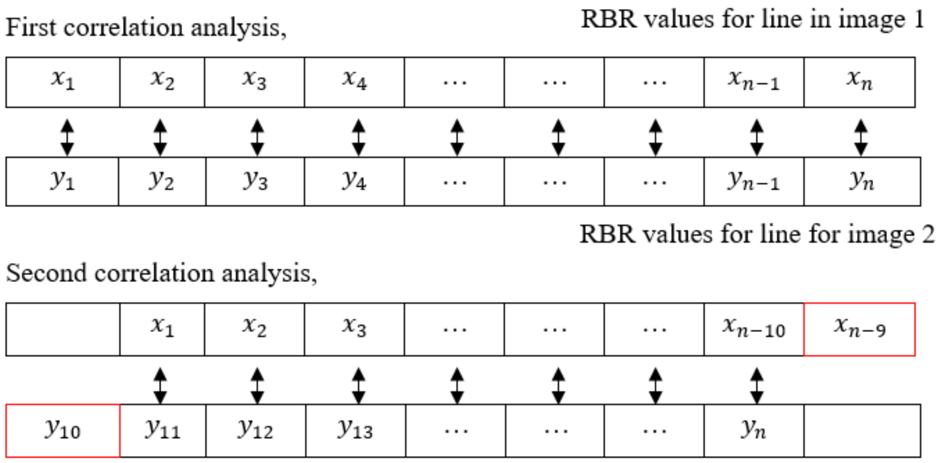

Figure 5 Visualization of correlation analysis.

Notice that the difference between each subsequent case is 10 pixels shifted to the right. A 10-pixel shift was chosen because a 1-pixel shift for Image 1 has significantly larger computational time for the sequence of correlation analyses when compared to a 10-pixel shift. Although a 1-pixel shift results in slightly better accuracy, considering the balance between accuracy and computational time, a 10-pixel shift for each subsequent case was chosen. Moreover, the RBR values in the red box for each subsequent case is not included in the correlation analysis since there were no more RBR values left (empty box) to correlate them with.

The Pearson correlation coefficient (see Eq. (2)) is used to calculate the correlation between the paired points of Image 1 and Image 2 (see Eq. (2), the paired points are shown by the double arrow).

$$Pearson\ Correlation\ Coefficient = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{2}$$

In this context, the calculated Pearson correlation coefficient is a single numeric value that represents the similarity between the RBR values of pixels of two images. The higher the similarity between the RBR values, the closer the RBR values in both images, and hence the closer the cloud position in Image 1 to the position of the same cloud in Image 2.

Upon completing the correlation analysis, the number of pixels travelled is determined through identifying the set of correlation analysis data that results in the highest correlation coefficient. In this research, cloud velocity is defined as the pixel distance travelled by a cloud between two images in a period of time, which can be obtained as follows:

$$Cloud\ Velocity = \frac{number\ of\ pixel\ traveled}{time\ difference} \tag{3}$$

The time difference used in this research was 60 seconds.

2.4 Cloud Moving Direction Calculation

However, the definition shown in Eq. (3) only represents the magnitude of the velocity, whereas the direction of the cloud movement is also essential to predict cloud cover. For example, a cloud moving directly to the sun will result in greater cloud cover, hence it will have a greater effect on the solar intensity [13]. In contrast, there is less effect on the solar intensity from clouds moving away from the sun. Therefore, it is necessary to introduce a new cloud moving direction angle to indicate the direction of cloud movement for different moving directions of clouds. The cloud moving direction is defined as the angle between line AB and line AC (see Figure 6).

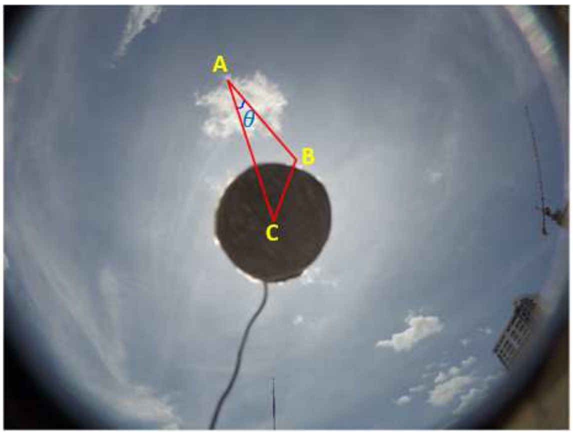

Figure 6 Geometrical visualization of cloud moving direction angle (from Figure 3(a)).

Using the cosine rule, the equation for the calculation of cloud moving direction angle can be obtained:

$$\theta = \cos^{-1}\left(\frac{c^2-a^2-b^2}{-2(a)(b)}\right) \tag{4}$$

where a = length between point A and point B, b = length between point A and point C, c = length between point B and point C, θ = angle between line AB and line AC.

2.5 Establishment of ANN Model

ANN was used to develop the forecast model. To establish the ANN network, the cloud velocity, cloud moving direction angle, and average solar radiation within a 1-minute time interval were used as input. The average solar radiation within the 1-minute time interval was calculated using Equation 5. This equation was used because the solar radiation data collected in this research were 1-minute based. Therefore, the average solar radiation was calculated to have a better representation of the overall solar radiation during that 1-minute interval.

$$Average\ solar\ radiation = \frac{SR_1 + SR_2}{2} \tag{5}$$

where, SR_1 = solar radiation intensity at the time of Image 1, SR_2 = solar radiation intensity at the time of Image 2.

Different combinations of available inputs were used to compare the accuracy of each type of input. The combination of inputs used is listed in Table 1.

Table 1 Combination of inputs used for the establishment of ANN.

Number	Input used
1	V
2	A
3	S
4	V, A
5	V, S
6	A, S
7	V, A, S

Where, V = cloud velocity, A = cloud moving direction angle, S = average solar radiation.

The desired outputs are the solar radiation intensity in 1, 2, 3, 4 and 5 minutes in advance of the time Image 2 was taken. For simplification, the recommended default settings shown in Table 2 were used in the network in this research. The overview of the ANN methodology is shown in Figure 7 below. NeuroShell 2 was used for the establishment of the ANN model. R-squared was calculated for each ANN model to estimate its forecasting accuracy.

Table 2 Recommended default settings of ANN.

Learning Rate	0.9
Momentum	0.3
Initial Weight	0.3

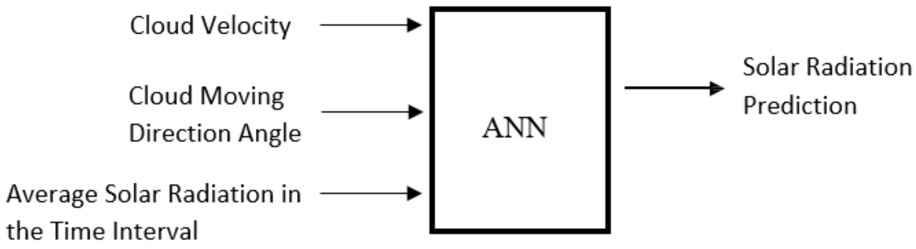

Figure 7 Overview of ANN methodology.

3 Results and Discussion

The case study presented in this paper begins with considering only a single cloud movement in each sky image. This was done to validate the effectiveness of the proposed methodology by limiting other uncertain factors, such as meteorological factors that may be introduced by multiple clouds. Thus, applying the proposed methodology on a single cloud in each sky image can provide a preliminary fundamental to validate the effectiveness of the proposed methodology and can also be used for further improvement of the method. The sample size used for this case study was 42 sets.

By using the recommended default settings listed in Table 2, the input combination listed in Table 1, and solar radiation intensity calculated from Eq. (5) as the output, seven ANN networks were established. The resulting R-squared values for each ANN model are shown in Table 3.

Table 3 R-squared values for each ANN model.

Input Combinations	Minutes in Advanced				
	1	2	3	4	5
V	-0.0603	0.0721	-0.0145	0.0113	0.0401
A	0.1226	0.2271	0.2716	0.2966	0.1985
S	0.5477	0.2323	0.0702	-0.2371	0.1694
V, A	0.0728	0.1180	0.0827	0.1035	-0.0326
V, S	0.5547	0.2927	0.2408	0.3408	0.2223
A, S	0.5455	0.3094	0.2360	0.0923	0.3575
V, A, S	0.5938	0.4719	0.5557	0.5208	0.5722

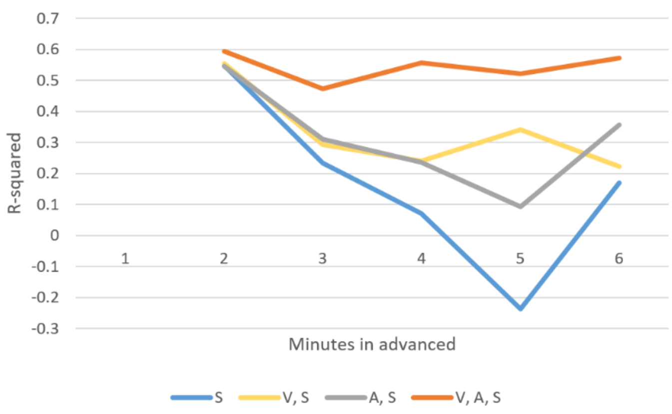

Figure 8 Graph of R-squared value against minutes in advance.

Table 4 and Figure 9 shows the percentage of improvement (difference in R-squared value) of various ANN models compared to the best performing ANN model, which was the model with V, A, and S. The percentage of improvement is based on the comparison of the R-squared value.

Table 4 Percentage of improvement.

	S to V,A,S	VS to V,A,S	AS to V,A,S
1 min in advanced	4.61 %	3.91 %	4.83 %
2 min in advanced	23.96 %	17.92 %	16.25 %
3 min in advanced	48.55 %	31.49%	31.97 %
4 min in advanced	75.79 %	18.00 %	42.85 %
5 min in advanced	40.28 %	34.99 %	21.47 %

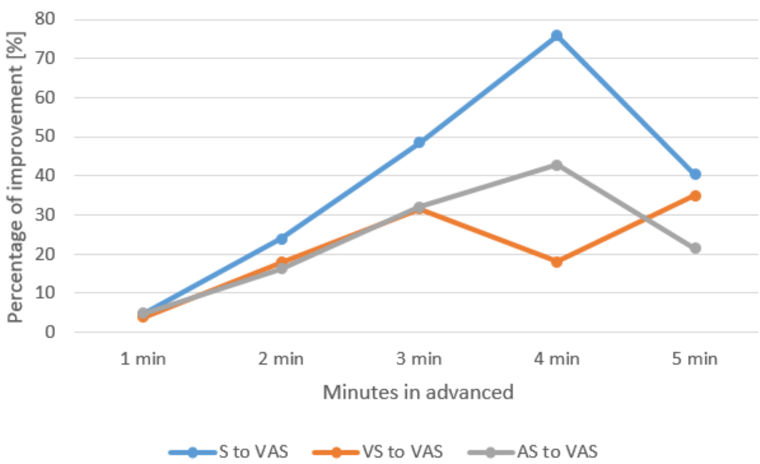

Figure 9 Graph of percentage of improvement against minutes in advance.

From Figure 8, the R-squared of the forecast model with 3 inputs was higher than that of the other models for every minute in advance. Thus, it can be concluded that the forecast model with all 3 inputs (cloud velocity, cloud moving direction angle, and average solar radiation) performed better than the other forecast models. This shows that by adding cloud velocity and moving direction, calculated with the proposed methodology, and including it in the establishment of ANN, the accuracy will improve. Notice that there are negative R-squared values for some of the forecast models; a negative R-squared value indicates that the performance of the established forecast model is even worse than the performance of the model with only the mean of all samples.

The performance improvement by adding cloud velocity and moving direction into the establishment of ANN is shown in Figure 9. Generally, there is not much improvement of predicting 1 minute in advance. But it is worth noticing that the improvement was increased drastically after predicting 2 minutes in advance, even reaching a highest point of 75.79% of improvement. This indicates that the methodology proposed has high potential in improving the accuracy of prediction models based on historical solar radiation data.

4 Conclusion

In this paper, a methodology for forecasting solar radiation based on cloud velocity calculated from ground based sky images was proposed. In the methodology, RBR values are used to calculate cloud velocity with less computational effort by analyzing only part of the pixels in the sky images.

By employing variables such as cloud velocity, cloud moving direction angle and average solar radiation into the forecast models (ANN), the solar radiation intensity can be predicted several minutes in advance fairly accurately. Furthermore, this methodology requires lower computational time since it only uses part of pixels in the sky images. Based on the R-squared analysis, it can be concluded that the ANN model with cloud velocity, cloud moving angle and average solar radiation as inputs showed the highest accuracy among the other combinations of inputs. The R-squared value was 0.59 with only a sample size of 42. The proposed model showed a highest improvement of 75.79% when compared to the model based on historical solar radiation data only.

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