Determination of Power Losses in Solar Panels Using Artificial Neural Network

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Abstract—The main purpose of this paper is on developing an intelligent system which provides real time monitoring and fault detection for solar panels. Utilizing artificial neural network technology, the solar panel fault detection system is capable of perceiving sun’s position in the sky and estimating the corresponding output power of a solar panel based on the algorithms derived by the artificial neural network which has been trained on solar data at several time intervals. The system is capable of operating in any geographical location providing 24-hour monitoring and fault detection as well as future power estimations for solar panels.

Keywords—Artificial neural networks, fault detection, photovoltaic cells, photovoltaic systems, solar energy, solar power generation.

I. INTRODUCTION

It is of prior importance to put effort into developing techniques of gaining benefit from renewable energy resources. The term renewable refers to the sustainability of the energy resource. According to Lynn (2010), “The Sun’s radiation beamed at us day by day, year by year, and century by century, is effectively free income to be used or ignored as we wish. This income is expected to flow for billions of years. Nothing is wasted or exhausted if we don’t use it because it is there anyway” [1]. The free and sustainable solar energy will be available for human use through the next centuries without causing any environmental damage to the planet earth.

This paper focuses on developing an Artificial Neural Network (ANN) based fault detection system which is capable of calculating sun’s position in the sky and estimating the corresponding solar panel output power.

In the following parts the details about collection and normalization of the solar data used to prepare the ANN training data sets will be given. When the ANN is implemented and trained, the solar data will also be used in execution of the fault detection system.

The solar panel fault detection system is developed using C programming language and the artificial neural network utilized in the system is implemented using the Fast Artificial Neural Network (FANN) library [2].

II. SUN’S POSITION DATA

As described in [3], the sun’s position in the sky is expressed by three different angles which are the Solar Altitude Angle, the Solar Azimuth Angle and the Solar Angle of Incidence. These three values are fed as inputs to the ANN which will be utilized in the solar panel fault detection system. The methods of calculation and normalization of each of the angles in order to make them ready to be fed as inputs to the ANN are described in the following sections. All the sun’s position data calculations are based on local solar time.

A. The Solar Altitude Angle

The Solar Altitude angle $\gamma_s$ indicates sun’s elevation from earth’s surface and is calculated by Eq.1:

$$\gamma_s = \sin^{-1}(\sin\varphi \sin \delta + \cos \varphi \cos \delta \cos \omega) \text{ Degrees} \quad (1)$$

Where,

$\varphi$ : The latitude of the observation point

$\delta$ : The solar declination angle

$\omega$ : The solar hour angle

It is observed that the solar altitude angle values range between -40 degrees to 90 degrees during a 24-hour period. The highest value of the solar altitude angle which optimally affects the performance of the solar panel is reached at 12:00 hrs and corresponds to the sun’s highest elevation.

Before feeding the value as an input to the ANN it is normalized between 0 and 1. The value 0 refers to the angle value that has the least effect on panel’s power output, which is 90 degrees and is reached at noon.

The normalization used to modify Eq.1 is given in Eq.2 and the result is given in Eq.3, which represents $\gamma_{s,input}$ that is passed as the first input to the artificial neural network.

$$\text{Normalized Value} = \frac{\text{Value} - \text{Minimum}}{\text{Max} - \text{Minimum}} \quad (2)$$

$$\gamma_{s,input} = \frac{\gamma_s + 40}{130} \quad (3)$$

As discussed in [3] the factor $j'$ indicates the effect of the Julian day number in the declination angle ($\delta$) calculation.
The normalized solar altitude angle calculation results over a 24-hour period on July 1st, 2012

Figure 1 shows the results of per minute calculations of $\gamma_{\text{S,input}}$ for constant latitude and different time angles over a 24-hour period for Julian day number 182 which refers to July 1st. As it is obvious from the figure, $\gamma_{\text{S,input}}$ almost reaches its optimal value 1 which refers to 90 degrees for $\gamma_{S}$ at 12:00 hrs on July 1st.

B. The Solar Azimuth Angle

The second value which is fed as input to the artificial neural network is the Solar Azimuth Angle. As described in [3] the solar azimuth angle indicates sun’s deviation from north direction and is represented by Eq.4:

$$
\begin{align*}
\alpha_{s} &= 180 - \cos^{-1}(\cos \alpha_{s}) \quad \text{If } \sin \alpha_{s} < 0 \\
\alpha_{s} &= 180 + \cos^{-1}(\cos \alpha_{s}) \quad \text{If } \sin \alpha_{s} > 0
\end{align*}
$$

Where,

$$
\cos \alpha_{s} = (\sin \varphi \sin \gamma_{s} - \sin \delta) / \cos \varphi \cos \gamma_{s}
$$

$$
\sin \alpha_{s} = \cos \alpha_{s} \sin \omega / \cos \gamma_{s}
$$

The effect of time angle ($\omega$) makes $\sin \alpha_{s}$ take on positive values from 12:00 to 00:00 hrs and negative values from 00:00 to 12:00 hrs, therefore Eq.4 is modified in the data collection system to calculate the solar azimuth angle $\sin \alpha_{s}$ for these two different periods of time.

The solar panel used for data collection is south oriented, therefore the values of the solar azimuth angle which represent the location of sun in south direction mostly affect the performance of the panel. Since Eq.4 represents sun’s deviation from north direction, it takes on 0 and 180 degrees when sun is located in north and south directions respectively. Therefore, again using Eq.2 we can normalize Eq.4 in the form of Eq.7-8:

For $\alpha_{s} < 180$,

$$\alpha_{s,input} = 1 - \frac{180 - \alpha_{s}}{180} \quad (7)$$

For $\alpha_{s} > 180$,

$$\alpha_{s,input} = 1 - \frac{\alpha_{s} - 180}{180} \quad (8)$$

Figure 2 shows the results of per minute calculations of $\alpha_{s,input}$ over a 24-hour period for July 1st using Eq.7-8. As it is obvious from the figure, $\alpha_{s,input}$ takes on its highest value 1 at 12:00 hrs which shows that the sun is located in south direction at noon. Since the solar panel is also headed in south direction, the value of $\alpha_{s,input}$ at noon refers to the situation in which the panel is located in front of sun and is expected to work with its maximum performance.

C. The Solar Incidence Angle

The third and last value to be passed as input to the ANN is the Solar Angle of Incidence ($\theta$). The solar angle of incidence is the angle between the sun’s radiations and a vector perpendicular to the solar panel’s surface. When the sun’s radiations are perpendicularly received on the solar panel’s surface, $\theta$ takes on its optimal value 0 degree. Like the solar altitude and azimuth angles, the solar angle of incidence which is represented by Eq.9 has a major role in solar panel output power estimations.

$$\theta = \cos^{-1} \left[ \frac{\cos(\beta) \cos(Z_{s}) + \sin(\beta) \sin(Z_{s}) \cos(\alpha_{m}))}{\cos(\alpha_{m})} \right] \quad (9)$$

Where,

- $\beta$: Tilt angle of the solar panel (45° in this case)
- $Z_{s}$: Zenith Angle of the Sun
- $\alpha_{m}$: Module azimuth angle (In this case: South = 180°)

And,
\[ Z_s = 90 - \gamma_s \]  

(10)

Similar to the first two inputs (\(Y_{s,input}\) and \(\alpha_{s,input}\)), it is desired to normalize the value of the solar angle of incidence between 0 and 1 before feeding it as the third input to the ANN. The normalized input value takes on 1 corresponding to 0º which is the optimal value of the angle of incidence and as this value moves towards 180º, the normalized input value decreases down to 0.

Again Eq.2 is used to normalize Eq.9 which results in Eq.11:

\[ \theta_{input} = 1 - \frac{\theta}{180} \]

(11)

Figure 3 shows the results of per minute calculations of \(\theta_{input}\) over a 24-hour period, again for the Julian day number 182 which refers to July 1st. As it is obvious from the figure, \(\theta_{input}\) takes on its maximum value on 12:00 hrs which indicates that sun’s radiations are perpendicularly received on the solar panel’s surface at noon, and decreases down to its minimum value at midnight.

III. SOLAR PANEL OUTPUT POWER

The solar panel used to collect data for the fault detection system is a 50x60 cm² monocrystalline silicon panel (\(P_{max}\): 40W, \(V_{OC}\): 21.6 V, \(I_{SC}\): 2.56 A) located at 17 meters above the sea level on the roof of the Electrical and Electronic Engineering Department, Eastern Mediterranean University at 35° 8' 51" N, 33° 53' 58" E. The panel is south oriented tilted 45 degrees.

The terminal voltage of the solar panel reaches \(V_{OC}\) in the early morning hours and makes it impossible to measure and monitor the changes in panel output characteristics as solar irradiance incidence increases. Therefore, the panel is connected to a power resistor which provides the possibility of accurate and sensitive monitoring of the scaled panel output characteristics.

![Fig. 3 The normalized solar angle of incidence calculation results over a 24-hour period on July 1st, 2012](image)

The output power is firstly used while the training data sets for the artificial neural network (ANN) are being prepared and then it is used to compare with the estimated output power after each execution of the ANN in the fault detection system (the details about training and execution of the ANN will be given in later parts). The corresponding time for solar panel output power measurements is the local time at the observation point.

An electronic circuit is constructed to measure the output power of the solar panel and transfer the data to a computer. The different parts of the solar panel output power measurement circuit consisting of (a) Microprocessor, (b) Max232, (c) Power Resistor and (d) Voltage Divider Circuit along with their connections are shown and labeled in Fig. 4.

The output power of the solar panel was firstly tracked and logged over a 24-hour period with a sample rate of 1 reading per minute. The system was designed to read the computer’s serial port which was connected to the circuit in Fig. 4, log the data referred to the output power of the solar panel along with the time of reading the port and wait for 60 seconds.

![Fig. 4 The Circuit Used for the Output Power Measurement of the Solar Panel](image)

![Fig. 5 Output power measured with 1 sample per minute for a 40W monocrystalline silicon solar panel over a 24-hour period on July 3rd, 2012](image)
The result of about 1400 times reading and logging the value of solar panel’s output power over a 24-hour period starting from 00:00 hrs on July 3rd, 2012 is shown in Fig. 5.

As it is obvious from Fig. 5, solar panel’s output power measured with 1 sample per minute is highly fluctuating. Logging the fluctuating power value in the artificial neural network training data sets would decrease the efficiency of the training process of the ANN and increase its training error. The solution to this problem is to increase the averaging rate of the measured output power.

At this point the system is modified to read the output power of the solar panel through computer’s serial port at 5 second intervals. After 12 readings is completed (which corresponds to 60 seconds reading time), the average value of the last 12 samples is logged along with the exact time at the moment. Figure 6 shows the results of about 1400 measurements of the solar panel’s output power with an averaging rate of 12 readings per minute over a 24-hour period on July 3rd, 2012.

As shown in Figure 6, increasing the averaging rate of the solar panel’s output power measurement decreases the fluctuations in the logged data and makes it ready to be passed into the artificial neural network training data sets. Similar to the input values, the output value also has to be normalized before being passed to the training data set.

IV. ARTIFICIAL NEURAL NETWORK TRAINING PROCESS

As previously mentioned, it is aimed to develop an artificial neural network (ANN) which receives the values of the solar altitude angle, the solar azimuth angle and the solar angle of incidence as inputs and derive the estimated solar panel output power corresponding to each set of input. The ANN needs to be trained with inputs and outputs collected formerly. After the training process completed, the ANN gets ready to derive proper outputs for the inputs given in training data set as well as generalizations for new inputs. The training process is done on a .data training file which is shown in Figure 7.

The first line in the training file indicates that the ANN goes through 1339 training paths with 3 inputs and 1 output. The next couple of lines consist of the input values which are \( y_{s, \text{input}} (3), \) \( \theta_{s, \text{input}} (7, 8) \) and \( \theta_{\text{input}} (11) \) in the first line and the normalized solar panel output value in the second line. These two lines represent the first training path for the ANN and are followed by 1338 other paths which are all formed in the same way with different input and output values.

The artificial neural network utilized in the solar panel fault detection system has a multilayer feed-forward architecture with a back-propagation algorithm. During the training process each training path is processed separately and inputs of each path are propagated through different layers of the network until they reach to the output layer. At this point the error of the training process is calculated with respect to the output specified to each input array in the training data set. After all the training paths are processed, the back-propagation algorithm is applied to adjust the weights on neurons in different layers of the network. The procedure continues until the training error falls below a preset threshold.
The architecture of the multilayer fully connected artificial neural network shown in Fig. 8 consists of an input layer, two hidden layers and an output layer. This ANN architecture with symmetric sigmoid activation function with steepness factor 1 is selected to be utilized in the solar panel fault detection system since it provides the lowest error during the training and execution phases.

Executing the training process, the ANN falls below the preset training error threshold 1.2×10^{-4} after 15215 epochs of back-propagation and at this point a .net file is created to be used for execution of the ANN with future inputs.

V. EXECUTION RESULTS OF THE PROPOSED SOLAR PANEL FAULT DETECTION SYSTEM

At this point, having the artificial neural network trained with collected solar data, the solar panel fault detection system is ready to be executed. When the system is run, it connects to the computer’s serial port to get the value of the solar panel output power every 5 seconds and calculate the average output power with 12 samples per minute. After calculating the average power for each minute, the system gets the time and calculates the values of γ_{input} (3), α_{input} (7, 8) and θ_{input} (11) and feeds them as inputs to the artificial neural network shown in Fig. 8.

The inputs propagate through the network layers to reach the output layer. After the execution of the ANN is completed the output value is reconstructed from the normalized form and logged as the estimated output power for the corresponding time. At this point the root mean square error between the estimated and the actually measured output power values are calculated and logged as a percentage error with respect to the measured output power value.

If the calculated percentage error value falls below a preset threshold, the execution window of the fault detection system produces the message “System Performance Check: Successful” along with the exact time, measured power value, estimated power value and the root mean square error value. On the other hand, if the percentage error value exceeds the threshold, the system reports the message “System Performance Check: Fault Detected” again along with the previously mentioned values.

The solar panel output power values (measured vs. estimated) and the root mean square error between the measured and the estimated power values over a 24-hour period on July 6th, 2012 which was a clear, sunny day are shown in Fig. 9.

Table I. shows the different values of the average percent RMSE between the measured and the estimated solar panel output power for different daylight time intervals from 1 up to 12 hours on a clear, sunny day (July 6th, 2012).

The daylight time interval 8:00-18:00 corresponds to the period in which the solar panel operates effectively and the solar panel fault detection system is executed within this interval providing overall %RMSE values between 3.17% and 8.40%. These values may be compared to the RMSE values for different models of irradiance estimation introduced in [4].

Nguyen [5] indicates that in a solar panel/module consisting of 10 sub-modules each containing 10 solar cells interconnected by 2 different connection types (Simple Series-Parallel and Total-Cross-Tied), the effect of 6 solar cells being shaded or damaged results in 17% to 48% overall power loss based on the locations and connection types of the shaded/damaged solar cells. Respecting the above, the 15% RMSE value between the measured and the estimated output power is decided as threshold for the solar panel fault detection system.

Setting the RMSE threshold for the solar panel fault detection system to 15% provides the possibility of detecting any failure higher than 6% in a solar panel’s surface [5].
TABLE I. AVERAGE PERCENTAGE RMSE BETWEEN THE MEASURED AND THE ESTIMATED OUTPUT POWER VALUES FOR DIFFERENT DAYLIGHT TIME INTERVALS ON JULY 6TH, 2012

<table>
<thead>
<tr>
<th>DAYLIGHT TIME INTERVAL (HOURS)</th>
<th>AVERAGE RMSE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12:30 – 13:30</td>
<td>3.309906</td>
</tr>
<tr>
<td>12:00 – 14:00</td>
<td>3.420657</td>
</tr>
<tr>
<td>11:30 – 14:30</td>
<td>3.188346</td>
</tr>
<tr>
<td>11:00 – 15:00</td>
<td>3.175156</td>
</tr>
<tr>
<td>10:30 – 15:30</td>
<td>3.175156</td>
</tr>
<tr>
<td>10:00 – 16:00</td>
<td>3.950062</td>
</tr>
<tr>
<td>9:30 – 16:30</td>
<td>4.602882</td>
</tr>
<tr>
<td>9:00 – 17:00</td>
<td>5.207249</td>
</tr>
<tr>
<td>8:30 – 17:30</td>
<td>5.554695</td>
</tr>
<tr>
<td>8:00 – 18:00</td>
<td>8.405882</td>
</tr>
</tbody>
</table>

VI. CONCLUSIONS

The artificial neural network based fault detection system provides 24-hour monitoring and real time fault detection of solar panels. The mechanism of the fault detection system relies on the position of the sun in the sky. During the data collection procedure, the sun’s position is calculated and recorded along with the corresponding solar panel output power in the artificial neural network training data sets. The ANN is trained with the solar training data sets and derives the algorithms that relate the solar panel output power to the position of the sun in the sky.

At this point the artificial neural network is capable of estimating the output power of the solar panel with respect to the sun’s position. The fault detection system is designed to measure the average output power of the solar panel with 12 samples per minute and compare it with the output power estimated by the ANN. If the root mean square error between the measured and the estimated output powers exceeds some preset threshold an error message is produced to report the RMSE value along with the measured and estimated output power values and system time.

Utilizing the solar panel fault detection system, any power loss due to damaged cells, shadows etc. is detected and reported immediately which increases the efficiency of the solar power stations and decreases the long term maintenance and support costs.

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REFERENCES