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Solar Photovoltaic Array's Shadow Evaluation Using Neural Network with On-Site Measurement

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Abstract- **This paper proposes a method to accurately predict the maximum output power of the solar photovoltaic arrays under the shadow conditions by using neural network, a combined method using the multilayer perceptrons feed forward network and the back-propagation algorithm. Using the solar irradiation levels, the ambient temperature and the sun's position angles as the input signals, and the maximum output power of the solar photovoltaic array as an output signal, the training data for the neural network is received by measurement on a particular time, when solar panel is shaded. After training, the neural network model's accuracy and generalization are verified by the test data. This model, which is called the shading function, is able to predict the shadow effects on the solar PV arrays for long term with low computational efforts.**

I. INTRODUCTION

Modeling and performance prediction of solar photovoltaic (PV) arrays is an important task in the design of solar PV systems. This includes understanding the environmental effects on performance, and in particular the output power of the array under various shading conditions. Specifically, the output power of a solar array strongly depends on the irradiance of sunlight. But, in some applications, such as solar power plants, building integrated photovoltaic, and portable solar tents, it is common for the solar PV to become illuminated non-uniformly. The cause of non-uniform illumination may be the shadows from: clouds, trees, booms, a neighbor's houses, or even a shadow of one solar array to the other one.

Fig. 1 shows the configuration of the shadow in the portable solar PV array. These new types of solar arrays are flexible and embedded into fabric. Campers, soldiers and recreationalists fold and carry them to remote locations to run electronics or charge batteries. Often the arrays are left alone all day to charge batteries and are placed in unusual locations including near trees, fences (as in Fig. 1) or are sometimes even wrapped around telephone poles. In these instances, non-uniform illumination across the PV occurs and can cause undesired effects in complicated nonlinear characteristic [1]:

1. The real power generated from the solar PV array may become significantly less than designed. At times, this may lead to a complete "loss of load."
2. The local hot spot in the shaded parts of the solar PV array can damage the solar cells.
3. There can be a long-term decrease in annual system performance due to shading. It is vital to understand this prior to installation in order to effectively determine whether the system is sufficiently cost efficient enough to install [2].

In order to include the effects of shadowing on solar PV arrays, conventional methods use an approach to determine the "shading factor," which is defined as the ratio of the non-shaded area to the total area of the solar arrays.

In real operating conditions, solar PV arrays are connected with Maximum Power Point Trackers to track maximum output power. The maximum output (MPP) power is often assumed linearly proportional to solar irradiance. So shading factors also can be used to calculate MPP power of shaded solar PV arrays.

In reality, it is difficult to accurately estimate this shading factor because shadows change their shape and move with time. This leads to several approaches to evaluate the shadow effects on those solar PV arrays:

- In the numerical method, the solar irradiance on all solar cells is modeled based on real time input data. The output power of the solar PV array at a given output voltage is then received by solving differential equations on small time-scales (second, minutes) [1], [3], [4]. This method requires the unrealistic number of sensors to measure the irradiance in each solar cell. Furthermore, accurate prediction of the maximum output power of solar PV systems for long term (days, months, years) is more challenging, due to difficulties in modeling the shaded area in the solar PV systems.
- In the photogram metric method, the position of obstacles and their shadow are estimated by using the triangulation with two photographs or more [5].
- Neural network method is used in [6], [7], [8] for predicting the dependence of maximum output power of solar PV arrays on environmental factors. However, these papers focus on estimating the performance of solar PV arrays under uniform illumination.
- In the combined method, the neural network prediction model uses training data created by the numerical method. The low accuracy is due to the low accuracy of the modeling shadow objects [9].

From the above discussion, there is not a simple and accurate method to define the shadow effects on shaded solar PV array for long term (seasonal or annual) in non-uniform illumination.

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Figure 1. A portable solar PV array under non-uniform shadow conditions.

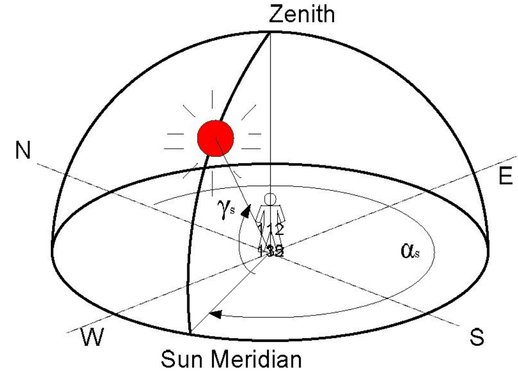

Figure 2. The sun's position at specific time at day

This paper proposes a novel method to define the function of relationship between the maximum output power (MPP) of the shaded solar PV array and the environmental factors, such as the solar irradiation levels, the sun's position angles and the ambient temperature. This function, which is similar to the shading factor, can fully characterize the shadow effects on the solar PV array for long term and is called the shading function. As such, the shading function can eliminate the inaccuracy caused by the complexity of the shading factor's calculation.

This method is related to the neural network method in [6], but now generalizes to non-uniform shadows and illuminations. Specifically, our approach proposes the following procedure to define the shading function for the solar PV array under shadow conditions:

1. The shadow ratio is characterized by the solar altitude and solar azimuth angles that are easily received from the information of the time of day for specific location. Thus, the input signals of neural network are the solar irradiation levels, the sun's position angles and the ambient temperature. The output signal of neural network is the maximum output power of the solar PV array.
2. The input signals and output signal of neural network are measured for the one-day period, when the solar PV array is shaded partly by any nearby object. The measured data set is divided into a training set, and a test set.
3. After the learning process of neural network, the test data prove the accuracy of the proposed model. The verified neural network model, the shading function, is able to predict the shadow effects on the solar PV arrays under any shadow conditions, i.e. with any solar irradiation levels, at any time of a day, when the solar array is shaded, and with different ambient temperature, for a long term and with low computational efforts.

II. THE PROPOSED SHADING ESTIMATION WITHOUT SHADING FACTOR'S MEASUREMENT

In the numerical method, the shadow effects on the solar PV arrays are estimated by the shading factor, measured as the ratio of the shaded area to the total area of the solar PV array. In the proposed method based on neural network, instead of using the shading factor calculation, we directly find the shading function that characterizes the relationship between the maximum output powers of the shaded solar PV arrays and the environmental factors: the horizontal solar irradiance, the sun's position, and the temperature:

$$P_{MAX} = f_{SHD}(Time, E, Temp) = f_{SHD}(\alpha_S, \gamma_S, I_{SC}, Temp) \quad (1)$$

Here, referring to Fig. 2, define the following variables: P_{MAX}- maximum output power of solar PV array, E-solar irradiation level, I_{SC}- short-circuit current, α_S, γ_S - solar position's angles, Temp- ambient temperature, Time- time of day, f_{SHD}- the shading function.

A neural network is an adaptive machine that resembles the human brain behavior. The neural network has a massively parallel distributed structure and the brain's ability to learn and generalize. Neural network can be used to detect and derive the meaning from complicated or imprecise data. To derive the relationship in (1), the inputs of neural network are measured data from environmental factors: the horizontal solar irradiance, the sun's position, and the ambient temperature. The output of neural network is the maximum output power of the shaded solar array. The neural network will process information, the large measured data of inputs and output, and learn from the data. The neural network will derive the function, which characterizes the relationship between the output and input signals in the form of matrix of weights. For future different environmental factors, the maximum output power of solar array under shadow conditions will be received in output of neural network by inputting the corresponding data of the time of day, solar irradiance and the ambient temperature.

The dependence of maximum output power of solar array on time, solar irradiation levels and ambient temperature is discussed below.

A. *The solar irradiance levels*

The average value, called the solar constant, E_o, of the solar irradiance measured outside the Earth's atmosphere on a surface perpendicular to the solar irradiations, is:

$$E_O = 1.367 \pm 2 W/m^2 \quad (2)$$

The value of solar irradiance E measured in the Earth's surface is usually smaller than the solar constant due to reflection by the atmosphere, absorption in the atmosphere, and scatterings.

In the solar photovoltaic array, the photo generated current or a short-circuit current is linearly proportional to the solar irradiation levels E and the coefficient C_0:

$$I_{PH} \approx I_{SC} = C_0 E \quad (3)$$

B. The position of the sun

The sun's position is defined by the two solar angles:

Sun's height (solar altitude or elevation) γ_S, solar or sun azimuth α_S is shown in Fig. 2.

These angles depend on the specific location of the solar PV array, the date, time, and time zone. The angle of solar altitude is calculated by the following equation:

The angle of solar altitude:

$$\gamma_S = \arcsin(\cos\omega.\cos\varphi.\cos\delta + \sin\varphi.\sin\delta) \quad (4)$$

The angle of solar azimuth:

If Solar time ≤12.00 hrs:

$$\alpha_S = 180^0 - \arccos\frac{\sin\gamma_S.\sin\varphi - \sin\delta}{\cos\gamma_S.\cos\varphi} \quad (5)$$

If Solar time ≥12.00 hrs:

$$\alpha_S = 180^0 + \arccos\frac{\sin\gamma_S.\sin\varphi - \sin\delta}{\cos\gamma_S.\cos\varphi} \quad (6)$$

Here δ is the solar declination, ω is the hour angle and φ is the latitude of the location

C. Temperature dependence

With the rising ambient temperatures, the open circuit voltage decreases significantly and the short circuit current increases lightly.

As a result, the maximum output power of the solar PV array will decrease.

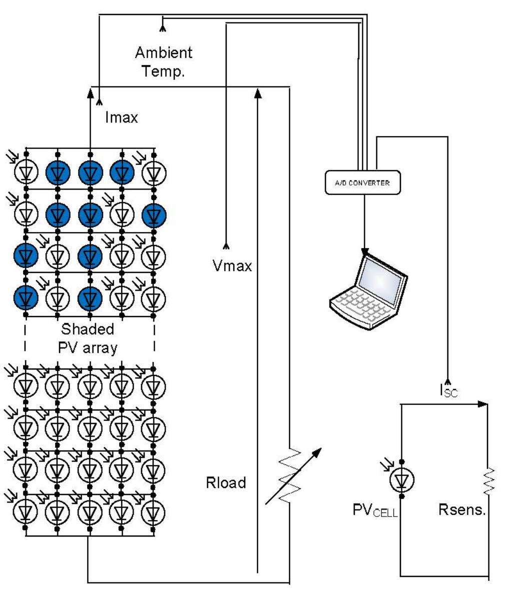

Figure 3. The input and output signals measurement circuit

D. The maximum output power

Maximum output power is measured by connecting the variable resistor R to the external circuit of the solar PV array. The value of R is defined by the following equation:

$$R_{LOAD} = \frac{V_{MPP}}{I_{MPP}} \quad (7)$$

here, V_{MPP} and I_{MPP} are the maximum output power voltage and the maximum output power current.

III. Experimental Setup

In this experiment, the solar PV array is outside and partly shaded by the nearby boom for some hours of day. Thus, the shadow is moving slowly with time.

The signals are measured as shown in Fig.3. Each diode presents the solar cell in total- cross- tied solar PV array. The darkened/colored diodes represent the shaded solar cells. Each shaded cell may be fully shaded or only partly shaded. So, the solar cells may have different shading factors. We assume that clouds have uniform effects on solar PV arrays and are not included in this experiment.

The shaded solar array is connected to the variable resistor R_{LOAD} to track maximum output power from solar array. One un-shaded solar PV cell is connected to very small R_{SENS} to measure the irradiation level (short-circuit current Isc).

The input signals are the short circuit current I_{SC}, and ambient temperature.

The output signal is maximum output power of the solar PV array

$$P_{MAX} = I_{MPP} \times V_{MPP} \quad (8)$$

The signals are measured with interval of 30 seconds at particular time, when solar panel is shaded. Using PC, the time of each measurement is recorded. The positions of the sun, the two angles of the sun, are calculated from the time of day based on the MATLAB software.

All measured data are divided to the training set and test set for neural network.

IV. Neural Network Structure

The above experimentally measured data set includes the input data set: the time, the solar irradiance, the ambient temperature and the output data set: the maximum output power of solar PV array. This data set is divided into training, and test subsets. The design of the neural network is as follows:

First, the input layer consist of source nodes equal the number of input signals, the output layer consist of nodes with equal number of output signals. A subset of measured data (the training set) is used to train the network by the back propagation algorithm. This part of network design is called learning.

Second, the performance of trained neural network is tested with the data from the test subset. The input signals of test subset are presented to the network. Then, the output of the network is compared with actual measured output.

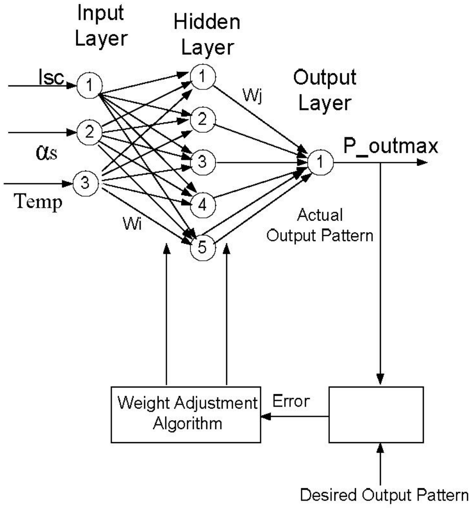

Figure 4. Neural network structure

In the specified neural network, the domain knowledge (here it is the relationship between the maximum output power of shaded solar PV array and the solar irradiation levels and the ambient temperature at a particular time) is captured by the value of free parameters (here they are the synaptic weights w_i and w_j and biases b_i and b_j) of the neural network. The weights are adjusted by back-propagation algorithm. An effective procedure for performing this operation is illustrated in Fig. 4.

A. Input signals correlation analysis

In some situations, the dimension of the input vector can be reduced by eliminating the components of the vectors that are highly correlated (redundant).

Table 1 shows the correlation between the input signals of the neural network. The short circuit current and the solar altitude have the correlation coefficient 0.98, so we can remove the solar altitude from the input signals vector.

TABLE I
THE CORRELATION BETWEEN THE INPUT SIGNALS

Correlation	Solar altitude	Solar azimuth	Isc	Temp.
Solar altitude	1			
Solar azimuth	-0.8355	1		
Isc	-0.9822	0.8580	1	
Temp.	-0.4120	-0.0559	0.3666	1

Fig. 4 shows that the input signals: the solar azimuth angle, the short circuit current, and the ambient temperature. The neural network has one output: maximum output power of solar PV array.

B. Neural network structure

Fig. 4 shows multiple layers of neurons with nonlinear transfer functions that allow the network to learn nonlinear and linear relationships between input and the corresponding output value. This is a two layer feed-forward configuration.

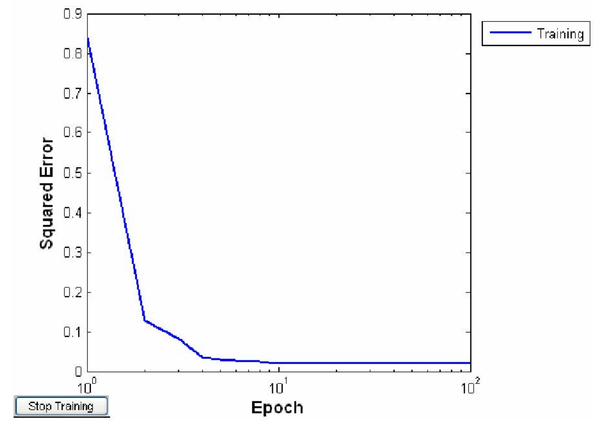

Figure 5. The squared error of the training process

C. The learning process

Once the network weights and biases have been initialized, the network is ready for training. The network is trained for function approximation. The training process requires a set of examples which include network inputs and target outputs. The experimental data is divided into training, and test subsets. We will take 70% of the data for the training set, 30% the test set.

During training, the weights and biases of the network are iteratively adjusted to minimize the network output estimation error. The default performance function for feed forward network is the mean square error MSE, the average squared error between the network outputs and the target outputs. Fig. 5 shows the squared errors after different epochs for training process. The error is calculated by equation:

$$Error = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(P_{MEASi} - P_{ESTi})^2 \qquad (9)$$

Here, P_{MEAS}, P_{EST}– the measured and estimated maximum output powers of solar PV array, N- the number of measurements in the training subset

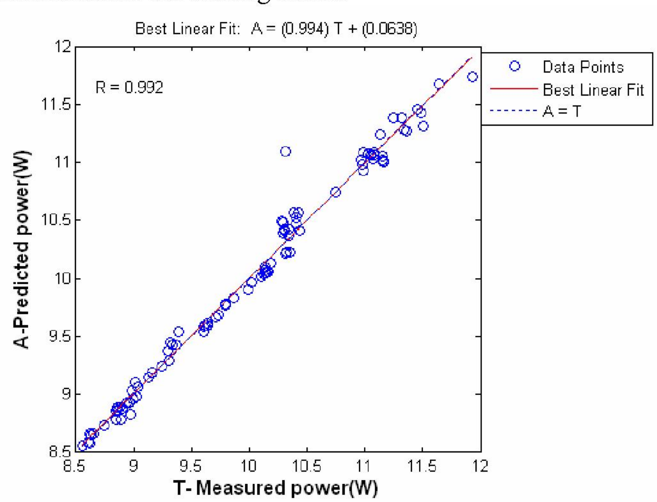

Figure 6. The network performance analysis

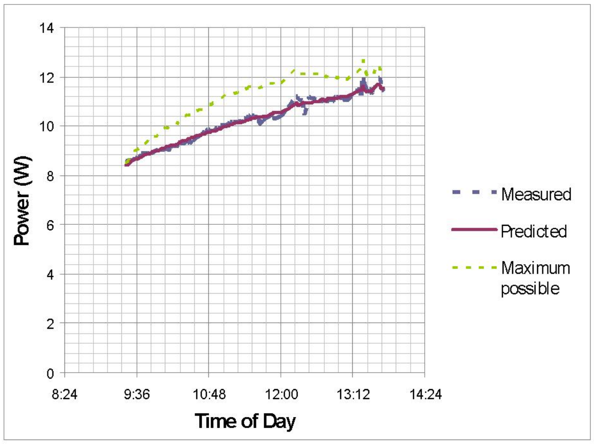

Figure 7. The measured and predicted output powers of solar PV arrays

The result here is acceptable, because the training set error and the test error have similar characteristics.

D. The generalization check

We can use data from the test subset to check the generalization of the network. The generalization characterizes the ability of the network to correctly map the data that was not involved in the learning. We can improve the generalization by using a larger network or regularization and early stopping method.

E. The performance analysis of the network response

To investigating the network response, we will put the test data set through the network and will perform a linear regression between the network outputs and the corresponding targets. Then, we perform a regression analysis between the network response and the corresponding targets. We pass the network output (predicted maximum output power) and the corresponding targets (measured maximum output power) to the linear regression analysis function. It returns three parameters shown in Fig. 6. If we have a perfect fit, the slope is close to 1, and y –intercept is near 0. The R=0.994 indicates that the output of the neural network track the targets well.

V. Analysis and Discusion

Fig. 7 shows the two predicted curves, maximum output powers of shaded and non-shaded solar PV array, and measured maximum output power of shaded solar PV array. We can see that the predicted maximum output power is very close to the measured one (dashed) for the non-uniform shading. The trained neural network consequently may be used for predicting the maximum output power for any other shadow conditions at any time of a day, with any levels of solar irradiance or ambient temperature.

VI. Conclusion

A neural network based model of the shadow effect on the maximum output power of the solar PV array is described. The maximum output power or maximum output power losses of the shaded solar PV array can be calculated based on shading function without a shading factor calculation.

The training data for the model, the shading function, can be easily collected on site by periodically measuring the maximum output power of solar PV arrays and measurable environmental factors over typical period of a day. The accuracy and generalization of the network are checked by comparing the simulation data to the measured data.

The model/ shading function can be employed to accurately predict the maximum output power of the solar PV array over long periods of time. The approach uses only readily available solar irradiation data at different times of a day, wherever the solar PV array is installed.

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