Performance Evaluation of Solar Photovoltaic Arrays Including Shadow Effects Using Neural Network

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Abstract- **This paper proposes a neural network based approach to estimating the maximum possible output power of a solar photovoltaic array under the non-uniform shadow conditions at a given geographic location. Taking the solar irradiation levels, the ambient temperature, and the Sun's position angles as inputs, a multilayer feed-forward neural network estimates the output power of the solar photovoltaic array. Training data for the neural network is generated by conducting a series of experiments on a shaded solar panel at different hours of a day for several days. After training the neural network, its accuracy and generalization properties are verified on test data. It is found that the neural network, which is an approximation of the actual shading function, is able to estimate the maximum possible output power of the solar PV arrays accurately. Further, the network is able to estimate the maximum output power for field data and gives rise to the possibility that the proposed approach can be used for making decision regarding the installation of solar PV arrays in the field.**

I. Introduction

The output power of a solar array strongly depends on the irradiance of the sunlight. In case of solar power plants, building-integrated photovoltaic panels, and portable solar tents, it is common for a solar PV to become illuminated non-uniformly. Fig. 1 shows some shadow configurations on portable solar PV arrays, which are flexible and embedded into fabric. Campers, soldiers and recreationalists fold and carry them to remote locations to run electronic devices or charge batteries. Often these arrays are placed near unusual locations including near trees, fences (as in Fig. 1) or are even wrapped around telephone poles. In these cases the PV arrays usually experience shadows from clouds, trees, booms, and neighboring houses. It is not uncommon that PV arrays are masked by shadow even from neighboring solar arrays as shown in Fig. 2. In these instances, non-uniform illumination across a PV array is likely to cause the following undesirable effects that are complicated and nonlinear: (a) the real power generated from a solar PV array may fall far below the designed level, which at times may lead to a complete "loss of load" [1]-[3]; (b) a local hot spot in the shaded parts of a solar PV array may damage the solar cells [4], [5]; (c) shading may cause long-term performance loss, hence the short-fall in the expected level of annual power production [6]-[8].

There are also a few approaches that have been proposed to reduce the effects of shadows on the solar PV systems by choosing the appropriate configurations [9] or by using reconfigurable solar PV arrays [10].

In order to include the effects of shadows on a solar PV array, conventional methods introduce a "shading factor," the ratio of the non-shaded area to the total area of the solar array [10], [11]. In reality, it is difficult to accurately estimate this shading factor because shadows change their shape and location with time.

Researchers have tried several approaches to evaluating the shadow effects on solar PV arrays. In numerical estimation methods, first the solar irradiance on all solar cells is computed based on real time input data, and then the output power of the solar PV array at a given output voltage is computed by solving differential equations on small time-scales (second, minutes) [9], [10]. This approach requires an unrealistic number of sensors to measure the irradiance on each solar cell; the accuracy of the estimated maximum output power of a solar PV system over extended periods of time (days, months, years) is less than satisfactory.

In the photogram metric method, the position of obstacles and their shadow are estimated through triangulation of two or more photographs [12]. Some other methods use neural networks [13]-[15] for relating the maximum output power of solar PV arrays to environmental factors. Neural network methods also have been proposed to size stand-alone solar PV systems [16] and to track maximum power from solar PV systems [17]-[19]. However, these methods focus on estimating the performance of solar PV arrays that are subject to uniform illumination. In another approach, a neural network is trained with the data created by the numerical method. The low accuracy of maximum power estimates in this approach is ascribed to the low accuracy of the shadow object models [20]. Overall there is not a simple and accurate method to determine the long-term effects of non-uniform illumination on solar PV arrays.

This paper proposes a neural network based approach to modeling the relationship between the maximum output power (MPP) of a shaded solar PV array and the environmental factors, such as solar irradiation levels, Sun's position angles, and ambient temperature under non-uniform illumination conditions. This neural-network-based function, like the shading factor, can characterize the shadow effects on

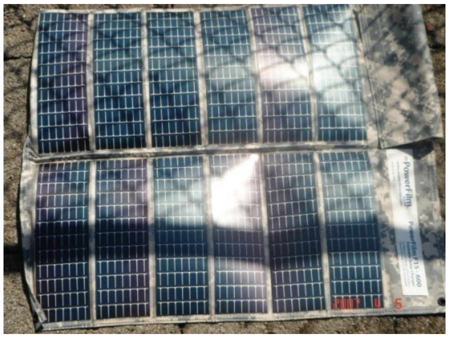

Fig. 1. Portable solar PV array under non-uniform shadow conditions

Fig. 2. One solar PV array cast shadow on another

the solar PV array on long-term basis. As such, the neural network model can eliminate the inaccuracy caused by the complexity of the shading factor's calculation.

Unlike an earlier work [14] which studied the effect of a uniform shadow on PV arrays, the current approach takes into account non-uniform shadows and non-uniform illumination conditions. Specifically, our approach proposes the following procedure:

1. The shadow ratio is characterized by solar altitude and solar azimuth angles that are easily determined from the time of day for a given geographic location. Thus, the inputs to the neural network are the solar irradiation levels, the Sun's position angles and the ambient temperature. The output of the neural network is the maximum output power of the solar PV array.
2. Experimental data is generated by taking measurements several times a day for several days when the solar PV array is shaded partially by a nearby object. The measured data set is divided into two sets, one for training the neural network and the other for testing the network. The neural network performance in estimating the maximum output power of the PV array is verified using test data.
3. Once the neural network is trained, it is used for predicting the output power of the solar PV arrays at any solar irradiation levels, at any time of day, and at different ambient temperatures, over a long time period with low computational efforts.

II. The Proposed Shading Estimation Without Measurement of Shading

To reduce the cost of electricity generation from solar PV systems, more and more large solar PV plants are built around the world. In recent years the total Megawatts of solar PV systems globally doubled. In order to make decisions regarding the installation of large solar PV systems, it is imperative that one is able to evaluate their performance. Conventionally, such decisions are made by looking into the performance ratio K. Flow chart in Fig. 3 shows the steps in this decision making process.

Taking into account solar insolation and ambient temperature data for a specific geographic location, the performance K ratio is calculated by the following equation [1]:

$$K = K_H \cdot K_{PH} \cdot K_{PT} \cdot K_{PA} \cdot K_{PM} \cdot K_B \cdot K_C \tag{1}$$

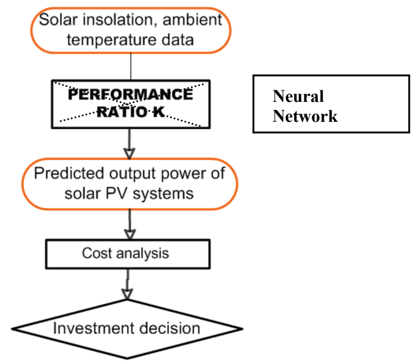

Fig. 3. Performance evaluation of solar PV system. The proposed neural network replaces the need to estimate the performance ratio of the solar panel.

The system performance ratio K is the most convenient value, since it is normalized by the site irradiation and the system size. It is not a single parameter but a product of various parameters:

K_H= irradiation modification factor caused by shadow and surfaces soil age

K_{PH}= incident-angle-dependent factor due to module glass structure reflection

K_{PT}= cell temperature factor due to the negative temperature coefficient of P_{MAX}

K_{PA}= array circuit factor that characterizes series-connected model mismatch and wiring resistive losses

K_{PM}= load matching factor caused by mismatch operation apart from P_{MAX} point

K_B= battery circuit factor including batteries and their peripheral losses

K_C= power conditioner circuit factor including power conditioner and their peripheral losses

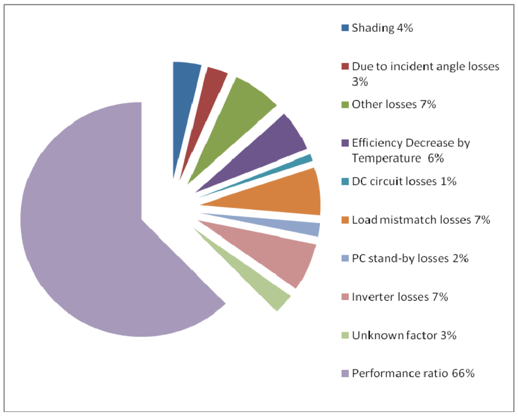

Fig. 4. Annual average values for system parameters at 187 Japanese field test sites for 4/1995-12/2001[1]

The above list of parameters is not an exhaustive collection of all the parameters that can theoretically come into picture, but a rather a set of parameters that majorly affect the system performance ratio K in PV systems in the field (see Fig. 4). When these parameters are evaluated, they are calculated as energy ratios instead of power ratios. From the above discussion, one can see that one needs shadow effects over a long period of time (year, month and day) for evaluating the performance of solar PV arrays.

In the proposed method we circumvent the need for the shading factor using a neural network-based shading function that characterizes the relationship between the maximum output powers of a shaded solar PV array and the environmental factors (see Fig. 3) and then make investment decision based on the predicted output power of solar PV systems. The neural network serves as a functional approximation to

$$P_{MAX} = f\,(t,E,T) \approx f\,(\alpha_S, \gamma_S, I_{SC}, T) \qquad (2)$$

where, P_{MAX} is the maximum output power of the solar PV array, E is the solar irradiation level, ISC is the short-circuit current, αs and γs are the solar position angles, T is the ambient temperature, t is the time of a day, and f is the shading function. In this paper, the shading function f is approximated using a multilayer feed-forward neural network, which is an adaptive learning machine that can learn from

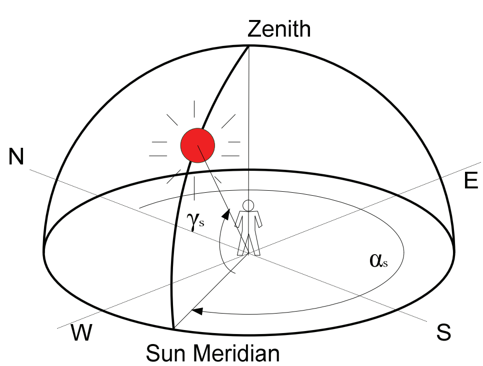

Fig. 5. The Sun's position at specific time at day [5]

a set of training. Through exposure to a set of measured input and output data, the neural network learns the shading function, which characterizes the relationship between the input signals (Sun's position angles, solar irradiation levels, and ambient temperature) and the output, i.e., the maximum output power of the solar array under shadow conditions. The solar irradiation levels, the Sun's position angles, ambient temperature, and the maximum output power of solar array are briefly described below:

Solar irradiance levels: The solar constant, E_0, of the solar irradiance is an average value measured outside the Earth's atmosphere on a surface perpendicular to the solar irradiations; it is given by:

$$E_o = 1367 \pm 2W/m^2 \qquad (3)$$

The value of solar irradiance E measured on the Earth's surface at a specific geographic location is usually smaller than E_0 due to the atmospheric reflection, absorption, and scattering. In a solar PV array, the photo-generated current or short-circuit current is linearly proportional to the solar irradiation levels E and the coefficient C_0:

$$I_{PH} \approx I_{SC} = C_0 E \qquad (4)$$

Position of the Sun: The Sun's position is defined by the Sun's height (solar altitude or elevation) γ_s, solar azimuth α_s (see Fig. 9). These angles depend on the specific location of the solar PV array, the time of a day, the day of a year, and the time zone. The angle of solar altitude is calculated by

$$\gamma_S = \arcsin\,(\,\cos\omega.\cos\varphi.\cos\delta + \sin\varphi.\sin\delta) \qquad (5)$$

If solar time ≤12.00 hrs, the angle of solar azimuth is computed from

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

or if solar time ≥12.00 hrs:

$$\alpha_S = 180^0 + \arccos\left(\frac{\sin\gamma_S.\sin\varphi - \sin\delta}{\cos\gamma_S.\cos\varphi}\right) \qquad (7)$$

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

Ambient temperature: 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 decreases with rising ambient temperature.

Maximum output power: The 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 as $R = V_{MPP}/I_{MPP}$, where, V_{MPP} and I_{MPP} are the maximum output power voltage and the maximum output power current respectively.

III. Experimental Setup

In proposed approach the shadow ratio is characterized by solar altitude and solar azimuth angles that can be easily determined from the time of a day for a specific geographic location. The inputs of the neural network are the solar irradiation levels, the Sun's position angles, and the ambient temperature. The maximum output power of the solar PV array is the output of the neural network. The input signals and output signal of neural network are measured several times of a day for several days, when the solar PV array is shaded partly by a nearby object. The trained neural network (surrogate shading function) is used for predicting the maximum possible output power the solar PV array produce under certain shadow conditions, at any solar irradiation levels, at any time of a day, and at different ambient temperatures, and over a long period of time.

In this experiment, the solar PV array is kept outdoors where it is shaded partially by a nearby boom for some hours of a day. The shadow is moving slowly with the time of a day. The experimental set up is shown is Fig.6. The signals measured in this experiment are shown in Fig.7. Each diode presents the solar cell in total-cross-tied solar PV array. The darkened diodes represent the shaded solar cells. Each shaded cell may be fully shaded or only partially shaded. So, the solar cells may have different shading factors. Assuming that clouds have a uniform effect on the solar PV array, their effect on the PV array is not considered in this experiment. The shaded solar array is connected to the variable resistor R_{LOAD} to track the maximum output power from the solar array. The maximum output power of the solar PV array is computed from $P_{MAX} = I_{MAX} \times V_{MAX}$. One un-shaded solar PV cell is connected to very small R_{SENS} to measure the irradiation level (short-circuit current I_{SC}). A thermocouple is used for measuring the ambient temperature.

The signals are measured at an interval of 30 seconds for a duration when the solar panel is shaded. The time of each measurement is recorded. The positions of the Sun in terms of the two angles are calculated from the time of a day using a MATLAB software function.

Fig.6. Experiment set up

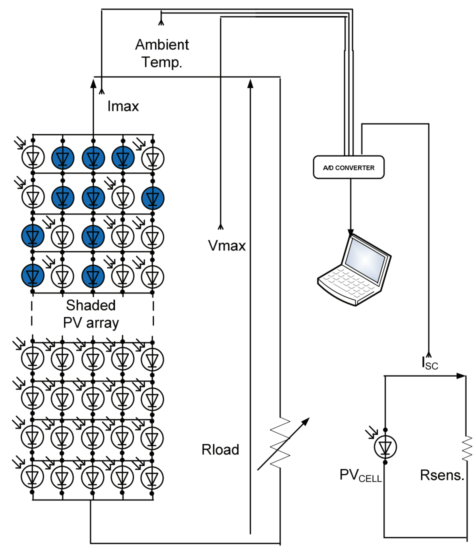

Fig.7. The input and output signals measurement circuit

IV. Training and Testing Neural Network

The data set measured from the experimental set up includes the time of a day, the solar irradiance, and ambient temperature as inputs to the neural network and the maximum output power of the solar PV array as the output. Totally there are 180 training pairs. The experimental data is divided into training set and test set: 80% of the data for the training set, 20% for the test set.

The training set was used for training the multilayer feed-forward neural network that approximate the shading function. The structure of the neural network is shown in Fig.8. It is trained using the back-propagation algorithm. The training process exposes the network to input vectors and the corresponding target values.

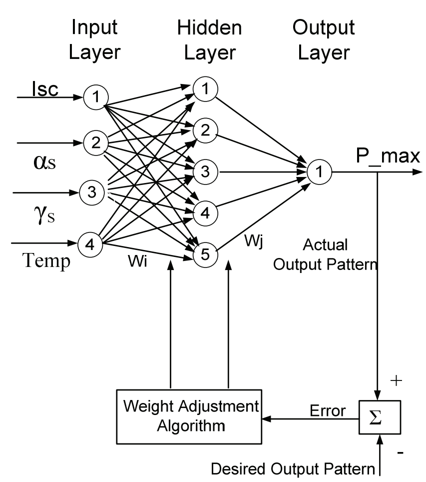

Fig. 8. Multilayer feed-forward neural network that approximate shading function

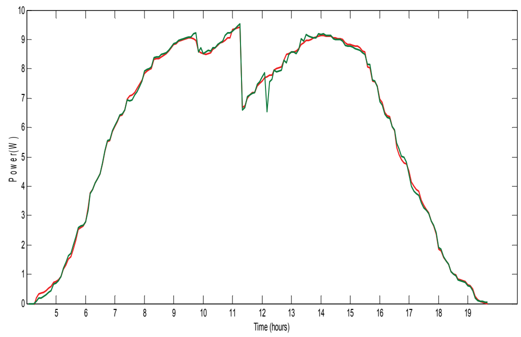

Fig.9. Predicted (dashed-red) vs. measured (solid-green) solar PV array output power (W) for test data.

The trained neural network captures the domain knowledge (shading function in this case) in its free parameters in the form of synaptic weights w_i and w_j and biases b_i and b_j.

The performance of the trained neural network as the approximator of the shading function is evaluated using the data from the test data set. The input signals of the test subset are presented to the network and then, the output of the network is compared with the actual measured output. This comparison is shown in Fig. 9. The figure shows two curves: (1) measured output power of a partially shadowed solar PV array; and (2) predicted maximum possible output power of the partially shaded solar PV array. We can see that the predicted output power is very close to the measured one (dashed) for the non-uniform shading. This result confirms that the trained neural network can be used for predicting the maximum possible output power of the solar array subject to similar conditions including geographic location, weather, and shadow conditions at any time of a day, with any levels of solar irradiance or ambient temperature.

V. Prediction of Output Power

Encouraged by the lab results described in the previous section, we now predict power output of the solar PV array using the field data.

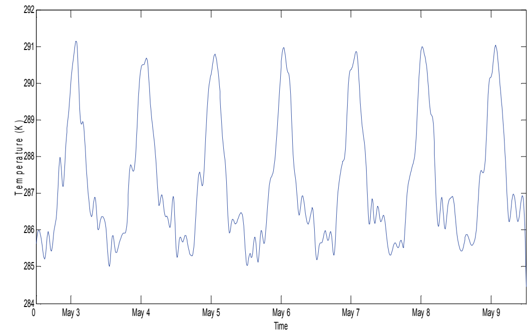

Fig. 11 Weekly ambient temperature (K)

Fig. 10 and Fig. 11 show the solar insolation and the ambient temperature at Logan Airport, Boston, MA for a week May 3-9, 2009. This is taken from an online database, which gives the hourly average measurements of the solar insolation and ambient temperature. Using a curve fitting technique, the data for the intermediate points are estimated through interpolation. By presenting I_{sc}, temperature, solar altitude γ_s (computed using Eq. (5)), and solar azimuth α_s (computed using Eq. (6) and (7)) to the trained neural network, we predicted the output power of solar PV system for a week. The results are shown in Fig. 12.

Though it is hard to verify the accuracy of the predicted output power of the solar PV system (if it were installed Logan Airport, Boston, MA), they seem reasonable and follow the pattern of solar insolation and ambient temperature. These results opens the possibility for using a neural network for predicting the output power of solar PV system for a given geographical location, provided we know the annual solar insolation and ambient temperature data for the location.

VI.CONCLUSION

This paper investigated a neural network-based shadowing function to predict maximum possible output power of a solar PV array which is like to experience non-uniform partial shading. The maximum output power or maximum output power losses of the shaded solar PV array is calculated based

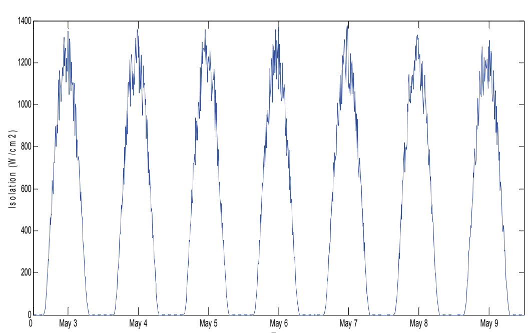

Fig. 10. Weekly solar insolation (W/m^2)

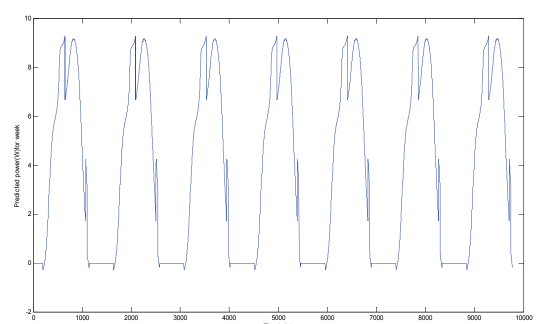

Fig. 12. PMPP prediction for a month (May 3-May 9, 2009)

on the shading function without the shading factor calculations.

The neural network training data is collected through an on-site experimentation by periodically measuring the maximum output power of the solar PV array and the environmental factors over typical period of a day, for several days. The accuracy and generalization abilities of the network are verified by comparing the neural network output to the measured data.

The results of this study indicate that the neural network based shading function can be employed to accurately predict the maximum output power of a solar PV array over long time horizons using only readily available local solar irradiation data at different times of a day, the Sun's position angles, and the ambient temperature for a given geographic location.

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