ESTIMATING SOLAR CELL OPERATING TEMPERATURE VIA DEEP NEURAL NETWORKS

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ABSTRACT: Saudi Arabia has great potential in clean energy production from photovoltaic installations. There are two main obstacles towards this goal which are related to the local climate: sandstorms and high ambient temperatures. Sandstorms are quite frequent in the region; scattered particles reduce solar irradiance and soil deposition on solar panels surface is significant, requiring regular cleaning. Furthermore, for most part of the year daily ambient temperatures can reach as high as 45 – 55 °C which are well above the range of STC for solar panels. These two factors can reduce the energy yield output of PV installations significantly. A priori knowledge and quantification of this efficiency loss can help design and assist in strategic planning to compensate and reduce the effects of local climate characteristics in energy yield output. In this work we aim on the estimation of the operating temperature of solar cells which is one of the key parameters for the assessment of the actual performance of photovoltaic panels. The proposed methodology is based on machine learning techniques and on Deep Neural Networks. The models provide excellent results and approximate solar cell operating temperature with less that 1 °C of accuracy.

1 INTRODUCTION

Over the past decades the world-wide market for solar photovoltaic (PV) technology has grown impressively. Every year the cumulative photovoltaic increases and it's estimated to be sufficient to supply about 1.5% of global electricity demand. Saudi Arabia belongs to a group of countries with the highest insolation worldwide, therefore, is an attractive market for PV implementation. The average energy from sunlight falling on Saudi Arabia is 2200 kWh/m^2, which allows a very competitive energy production cost. Even though Saudi Arabia receives a high level of solar insolation around the year, successful deployment of PV technologies can be challenging due to local weather conditions. Dust storms are frequent in the region, causing soling on the panel surface and reducing sunlight radiation intensity. In addition, the combination of increased ambient temperatures and high levels of solar radiation pose additional challenges in PV module energy yield performance. These two factors can reduce the energy yield output of PV installations significantly. A priori knowledge and quantification of this efficiency loss can help design and assist in strategic planning to compensate and reduce the effects of local climate characteristics in energy yield output.

In the literature there are several models for estimating the PV module operating temperature. These models are mathematical formulas usually derived from a data fitting process and use various parameters to provide a prediction. A set of models use electrical characteristics of the module, e.g., V_{oc} and/or I_{sc}. Another group of models, use parameters which, in general, are available a priori, such as air temperature (T_{air}), solar irradiance (G_{irr}), wind velocity (W_{vlc}) and efficiency of the module (η_{ref}). For a comprehensive review of these models, we refer the reader to [2,3] and the references therein. In [4] the authors used a some of these models to forecast module temperature by a nonlinear least square fitting process.

In this study, we propose two different methods for estimating solar cell operating temperature. The main ingredient in our approach is to use machine learning techniques. Our model is based on Deep Neural Networks (DNN). The input vector in the DNN consists of solar cell parameters and/or environmental factors which are known either apriori or aposteriori. The sole output of the DNN is the forecasting solar cell temperature.

2 EXPERIMENTAL SETUP – DATA ACQUISITION

The testing site is the New Energy Oasis (NEO) test field near the Red Sea coast (22.30 N, 39.10 E), located in KAUST, Thuwal, Saudi Arabia. This is a challenging location for PV installation since ambient temperature can reach values as high as 45-50 °C, which are far beyond the standard testing conditions (STC) range. The system consists of a monofacial PV panel of AlBSF technology an IV measuring system with radiation sensors and individual thermocouples which measure the temperature at the back of the module. The module consists of 60 solar cells, nominal efficiency is 14.5% at 45.7 °C NOCT, and maximum power of 240W. The measurements cover a period of ten days 28/03 – 06/04/2018, with samples every 10min.

3 METHODOLOGY

We propose a machine learning approach to estimate the solar cell operating temperature. The base model that we use is a Deep Neural Network (DNN) with an input vector consisting of five components, several hidden layers, and neurons and with a single output. We propose two methods that they differ in the kind of input parameters used in DNN. The first method (Method 1) uses as input the ambient temperature (T_{air}, ºC), the solar irradiance (G_{irr}, W/m^2), wind velocity (W_{vlc}, m/s), open circuit voltage (V_{oc}, V) and short circuit current (J_{sc}, A). This method uses actual/online measurements of solar cell's performance. In the second method (Method 2) we replace V_{oc} and J_{sc} by two manufacturing parameters of the panel namely, the T_{NOCT} value and module efficiency η_{ref}. The main advantage of the second method is that all input values can be known apriori. The sole output of both DNNs is the forecasting solar cell temperature.
We have tested the two DNNs depending on the input parameters used: (T_{air}, G_{irr}, W_{vlc}, V_{oc}, J_{sc}) for Method 1 and (T_{air}, G_{irr}, W_{vlc}, T_{NOCT}, η_{ref}) for Method 2. In both methods the first three parameters are the same and refer to atmospheric factors which can be obtained from well-known databases e.g., [1] in case local meteorological data are not available. The last two parameters in Method 1 are V_{oc}, J_{sc} which under operating conditions they might not be possible to acquire, while Method 2 uses T_{NOCT} and η_{ref} which are provided by the solar cell manufacturer. In [5] the authors consider a single hidden layer DNN with a six-component input vector which consists of with the same parameters as Method 1 plus the value of the produced power. The authors in [6] use also a single hidden layer DNN with a two-component input vector consisting only with (T_{air}, G_{irr}).

4 RESULTS

Before feeding the data to the DNN they were scaled-normalized so they all mapped to [0,1]. The DNN was built using Python 3.8 with an in-house code using stochastic gradient descent as the optimizing algorithm and a fixed learning rate. The number of hidden layers and neurons in the DNN they were kept as parameters to test their effect in the accuracy of the model. The training set was comprised by 70% of the data and the rest was used for validation-testing. It's worth mentioning that even with 30% of the data as a training set the Mean Absolute Error (MAE) in the testing set was below 1 ºC, showing the robustness of the method. Tables I, II show the MAEs on the testing set for both methods for a range of values of hidden layers (HL) and neurons (NR).

Table I : MAE on the testing set for Method 1

	Method 1: MAE's (ºC)			
NR/HL	2	3	4	5
5	0.711	0.623	0.602	0.609
10	0.589	0.578	0.532	0.447
20	0.619	0.629	0.392	0.396
40	0.567	0.530	0.322	0.229

Table II : MAE on the testing set for Method 2

	Method 2: MAE's (ºC)			
NR/HL	2	3	4	5
5	1.233	1.182	1.074	1.109
10	1.106	0.863	0.945	0.806
20	0.928	0.609	0.564	0.471
40	0.963	0.604	0.475	0.424

The first observation from Tables I, II is that for both methods the MAE decreases as the number of HL and neurons increase reaching a limiting value. The second observation is that MEA in Method 2 is larger that of Method 1. This expected since Method 1 uses actual values of V_{oc}, J_{sc} accounting for the actual cell operating conditions, in contrast to Method 2 which all its parameters are known apriori. Figure 1 shows the comparison between the prediction (blue dotted line) of Method 1 with 2 HL and 5 neurons on each node and the experimental values (solid red line) for the whole dataset. In this case we have MAE=0.889 ºC. The training time for the DNN with 5HL and 40 neurons was less than 1min for an MAE of about 1 ºC. Smaller training times can be achieved using one of the standard accelerating techniques for the stochastic gradient descent algorithm, e.g., Adam, [8]. The same DNN was build using *Tensorflow* computational framework, [7] for purely comparative purposes. For the same set of parameters, the in-house code and *Tensorflow* provided very similar results differing only on the execution time.

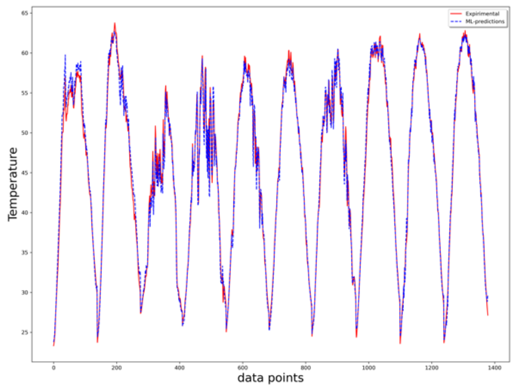

Figure 1: Method 1: 2HL, 5NR, Experimental Data (Red), DNN Model (Blue).

5 CONCLUSIONS

In this study we have developed machine learning techniques for estimating the operating temperature of solar cells. We have used DNNs with various number of layers and neurons. Two different approaches were used in terms of the kind of input data for these DNNs. Both methods produced excellent results in predicting solar cell's operating temperature. The first method that uses ambient factors and electrical characteristics produces the best results. The second method uses ambient data and parameters known apriori produced comparable results.

Both methods performed well with the differences between model predictions and actual measurements were small, less than one degree Celsius, for both methods.

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REFERENCES

[1] https://re.jrc.ec.europa.eu/pvg_tools/en/
[2] A.Q. Jakhrani, A.K. Othman, A.K., A.R. Rigit, S.R. Samo, World Applied Sciences Journal (2011), 14, 1–8.
[3] C. Coskun, U. Toygar, O. Sarpdag, Z. Oktay, Journal of Cleaner Production (2017), 164, 1474–1485.
[4] Th. Katsaounis, K. Kotsovos, I. Gereige, A. Basaheeh, M. Abdullah, A. Khayat, E. Al-Habshi, A. Al-Saggaf, A.E. Tzavaras, A. E. Renewable Energy (2019), 143, 1285–1298.
[5] G. Ciulla, L.V. Brano, E. Moreci, International Journal of Photoenergy 2013, (2013), 1–10.
[6] I. Ceylan, O. Erkaymaz, E. Gedik, A.E. Gürel,. Case Studies in Thermal Engineering (2014), 3, 11–20.
[7] https://www.tensorflow.org/
[8] M.J. Kochenderfer, T.A. Wheeler, Algorithms for Optimization; (2019); pp. 1–521, MIT Press.