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ESTIMATION OF PV MODULE SURFACE TEMPERATURE USING ARTIFICIAL NEURAL NETWORKS

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Abstract

This study aimed to use the artificial neural network (ANN) method to estimate the surface temperature of a photovoltaic (PV) panel. Using the experimentally obtained PV data, the accuracy of the ANN model was evaluated. To train the artificial neural network (ANN), outer temperature solar radiation and wind speed values were inputs and surface temperature was an output. The ANN was used to estimate PV panel surface temperature. Using the Levenberg-Marquardt (LM) algorithm the feed forward artificial neural network was trained. Two back propagation type ANN algorithms were used and their performance was compared with the estimate from the LM algorithm. To train the artificial neural network, experimental data were used for two thirds with the remaining third used for testing. Additionally scaled conjugate gradient (SCG) back propagation and resilient back propagation (RB) type ANN algorithms were used for comparison with the LM algorithm. The performances of these three types of artificial neural network were compared and mean error rates of between 0.005962 and 0.012177% were obtained. The best estimate was produced by the LM algorithm. Estimation of PV surface temperature with artificial neural networks provides better results than conventional correlation methods. This study showed that artificial neural networks may be effectively used to estimate PV surface temperature.
Keywords: Photovoltaic panel, Outer temperature, Solar radiation, Wind speed, Artificial neural networks

YAPAY SİNİR AĞLARI İLE PV MODÜL YÜZEY SICAKLIĞININ TAHMİNİ

Özet

Bu çalışmada, yapay sinir ağları (YSA) yöntemi kullanarak bir fotovoltaik (PV) panel yüzey sıcaklığının tahmininin yapılması amaçlanmaktadır. Deneysel olarak elde edilen PV verileri kullanılarak YSA'nın modelleme doğruluğu değerlendirilmiştir. Yapay Sinir Ağlarını (YSA) eğitmek için, dış sıcaklık, güneş radyasyonu ve rüzgâr hızı değerleri girdi ve yüzey sıcaklığı çıktı olarak kullanılmıştır. YSA PV panel yüzey sıcaklığının tahmini için kullanılmıştır. Leveberg-Marquardt (LM) algoritmaları kullanılarak ileri besleme tipi yapay sinir ağları ile eğitilmiştir. İki tane geri yayılım (backpropagation) ağ tipi YSA algoritması da kullanışmıştır ve onların performansları LM algoritmasının tahmini ile karşılaştırılmıştır. Yapay sinir ağının eğitilmesi için deneysel verilerin üçte ikisi ve geri kalan üçte biri ise test için kullanılmıştır. Ayrıca, Scaled Conjugate Gradient (SCG) Backpropagation ve Resilient Backpropagation (RB) tipi YSA algoritmaları LM algortimasının performansı ile karşılaştırılması için kullanılmıştır.Bu üç tip yapay sinir ağları algoritmalarının performansı karşılaştırılmıştır ve ortalama hata oranları %0.012177 ila %0.005962 aralığında elde edilmiştir. En iyi tahmini LM algoritması vermektedir. Yapay sinir ağlarının PV yüzey sıcaklığı tahmininde, konvansiyonel bağıntı metotlarından daha iyi sonuç vermiştir. Bu çalışma, PV yüzey sıcaklığını tahmin etmek için yapay sinir ağlarının etkili bir şeklide kullanılabileceğini göstermiştir.
Anahtar Kelimeler: Fotovoltaik panel, dış sıcaklık, güneş radyasyonu, rüzgâr hızı, yapay sinir ağları.

1 Introduction

Photovoltaic solar cells are devices that transform solar energy as sunlight (photons) falling on them into DC electric current using semi-conductor materials such as silicon, gallium, arsenide, cadmium telluride or copper indium dieseline during this process. Generally their surfaces have square, rectangular or circular shape with the area of solar cells about 100, 156 or 243 cm² and thickness between 0.2-0.4 mm. Depending on the structure, solar cells work with productivity between 5 and 20% [1].

It is known that increasing surface temperatures of photovoltaic panels negatively affects electricity production. When the literature on this topic is examined, there are many studies aiming to estimate and reduce surface temperatures.

A study by Jones and Underwood [2] attempted to estimate the PV module temperature based on solar radiation. They presented the results of tests of their calculation method with real data. Alonso Garcı and Balenzategui [3] in a study researched the effect of outer temperature and radiation on the panel surface temperature. The formula identified in their study is given below [3]:

$$T_M = T_{amb} + (NOCT - 20) \cdot \frac{E}{800} \quad (1)$$

In Equation (1) T_M is module temperature, T_{amb} is temperature of the outer environment, E is solar radiation and $NOCT$ is nominal operating cell temperature.

The study by Skoplaki and Palyvos [4] investigated in detail 13 different formulations [5-17] estimating PV module temperature in the literature.
ANNs may be used to estimate or classify problems. ANNs are formed by a mass of interconnected nodes called neurons, inspired by biological neurons. These neurons form a network architecture through their interconnections. ANNs may use multiple layers containing multiple hidden nodes [18].
This study used three types of ANN algorithms to identify system failures. To model the considered system, the Levenberg-Marquardt (LM) algorithm, scaled conjugate gradient backpropagation (SCG) and resilient backpropagation (RB) algorithms were used [18].

2 System Description

This study completed analyses for a solar-energy supported power station in the central Anatolia region. Due to trade restrictions on the company, results are given with capacity reduced to 500 kW. The measurement period covers the years 2013 and 2014. Measurements of the system included global radiation reaching panels, outer temperature, panel surface temperature, wind speed, voltage and current values. Taking account of the period from sunrise to sunset during the year, mean instant solar radiation values were measured as 398 Watt/m². Linked to the daytime period of days, the mean instant solar radiation value was modeled by the study team and is given in the equation below

$$I_D = 0.124 + 2.9\cdot 10^{-4}\cdot d + 5.99\cdot 10^{-5}\cdot d^2 - 3.39\cdot 10^{-7}\cdot d^3 + 4.73\cdot 10^{-10}\cdot d^4 \qquad (2)$$

In Equation (2) d is the number of the day with count starting on January 1st. While the first day of January is d=1, for the last day of December this value is 365 in the formula.

3 System Analysis

It was identified that during one year the power station provided 4557 hours of electricity production. With 500kW PV capacity, electricity production had an hourly mean of 118.8 kWh. On a daily basis the 500kW PV capacity system reached a maximum of 3.5 MWh/day. Figure 1 presents the distribution of electricity production on a daily basis. On the same figure, the daily mean electricity production has a parabola form. When mean values are considered, the maximum production level possible reaches 2.9 MWh/day.

The results of investigations on an hourly basis show the highest electricity production occurred between 12.00 and 13.00. In this period, electricity production of a total of 91.26 MWh/year was identified. As seen in Figure 2, between the hours of 07.00 and 20.00 values varied from 10 to 90 MWh/year. Due to system losses, the maximum capacity in operation is 86.5%. On a yearly basis the capacity operating rates are given in Figure 3. Capacity operating rates exhibit a balanced and narrow distribution between 15 and 80%. Mean capacity operating values reached 31.36%.

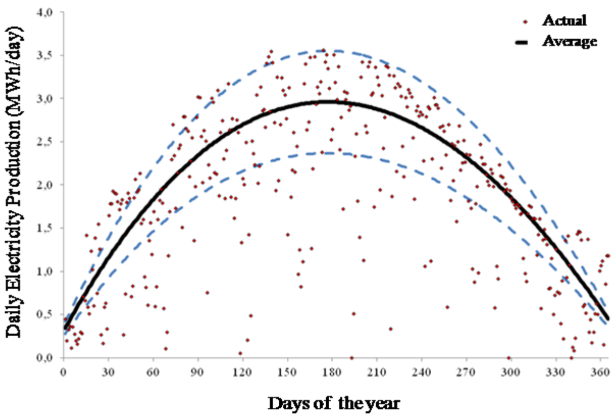

Figure1.Distribution of daily electricity production

There are three important parameters affecting the surface temperature of the panel. These are, in order, outer temperature, solar radiation and wind speed. With increases in outer environment temperature and solar radiation, panel surface temperature rises. Contrary to this, increased wind speed produces a reduction in panel surface temperature. The variation in panel surface temperature with outer temperature may be seen in Figure 4. The band of panel surface temperature has a fluctuating increase. The reason for this fluctuation is due to the most important factors of solar radiation and wind speed. The effects of the three important parameters on panel surface temperature are shown in a single figure in Figure 7.

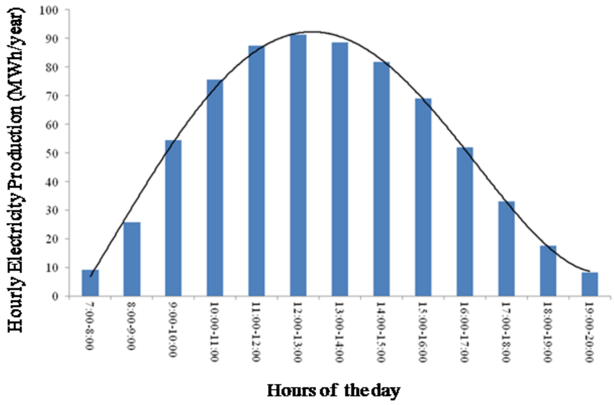

Figure2.Distribution of daily electricity production

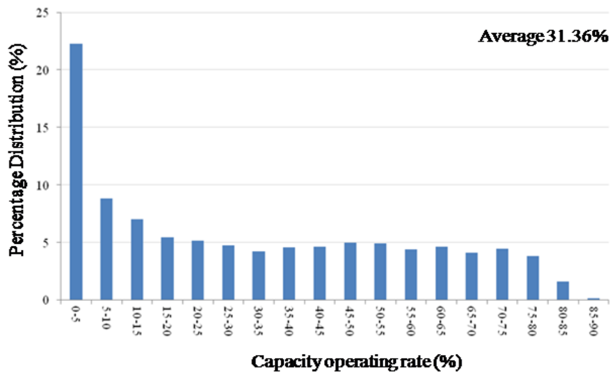

Figure3.Distribution of hourly electricity consumption for one year

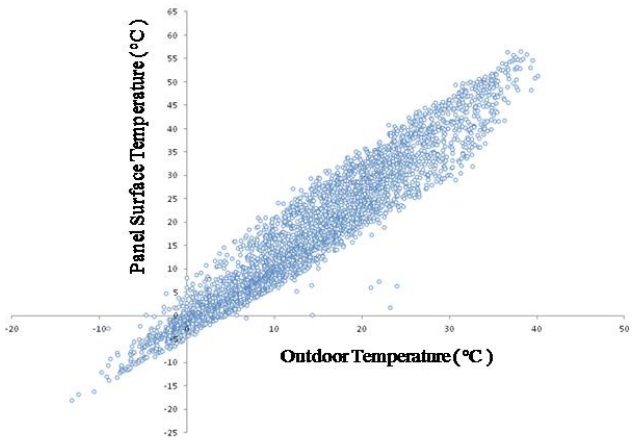

Figure4.Variation in panel surface temperature according to outer temperature

This study attempted to provide estimates of PV module surface temperature using both artificial neural networks and formula. In terms of formulation, the following approach is presented in the literature.

$$T_{PV} = 1.4 \cdot T_d + 0.01 \cdot (S_R - 500) - V^{0.8} \quad (3)$$

In Equation (3) T_{PV} is panel surface temperature (°C), T_d is temperature of the outer environment (°C), S_R is solar radiation value (Watt/m2) and 'V' is wind speed (m/s).

To more easily understand the calculations a simple analysis is given below. If an example is necessary, with conditions of outer temperature of 25 °C, solar radiation of 800 Watt/m2, and wind speed of 3 m/s, we can find the temperature of the panel in the following way:

$$T_{PV} = 1.4 \cdot T_d + 0.01 \cdot (S_R - 500) - V^{0.8}$$

$$T_{PV} = 1.4 \cdot (25) + 0.01 \cdot (800 - 500) - (3)^{0.8} = 35.6$$

4 Results

Experimental studies completed in 2013 and 2014 obtained a data set of 4200 points with measurements at 10 minute intervals in the hours of sunlight. The obtained experimental data used an artificial neural network (ANN) to model photovoltaic (PV) panel surface temperature. The results of this modeling estimated optimum results. Input nodes in the ANN network architecture were temperature of the outer environment (Tave), solar radiation (Rday) and wind speed (v_{wind}) with the output node of PV surface temperature (T_{PV}). Different amounts (1-40) of hidden nodes were used to estimate the most appropriate result for T_{PV} values. The trained data were tested to assess the ANN performance. Generally, estimates from test data have comparatively more errors than training data. According to the target data interval, the mean percentage error in output values for each training and test data can be described as [18]:

$$H_{ave} = \frac{1}{n} \frac{\sum_{i=0}^{n} \left| A^d - A^t \right|}{\left| A^d_{max} - A^t_{min} \right|} \quad (4)$$

In Equation (4), A^d is experimental data, A^t is estimated result and n is the number of data.

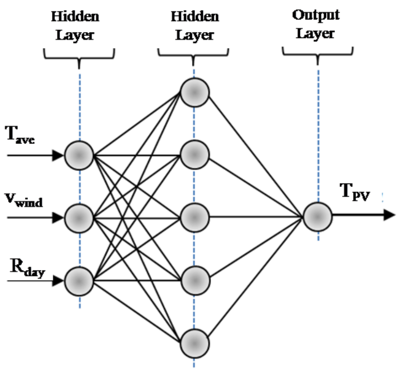

Figure5.Variation in panel surface temperature according to outer temperature

i) Modeling completed with artificial neural networks used the Levenberg-Marquardt algorithm (LM), scaled conjugate gradient backpropagation algorithm (SCG) and resilient backpropagation algorithm (RB) methods. The success of the modeling is the best test results. Accordingly, the test results of the ANN algorithms, respectively, were 34, 24 and 16 hidden nodes producing mean error values of 0.005962, 0.0075296 and 0.0083252. A section of the mean error rates from training and test results of hidden nodes producing the best results for LM, SCG and RB type ANN algorithms is given in Table 1. From within the LM, SCG and RB ANN models used for modeling, the best modeling results were reached with the LM algorithm. The error value reached with this algorithm was at the level of 0.005962 for 34 nodes. The variation in error rates for numbers of hidden nodes in the three models is graphically presented in Figure 6. According to the experimental and estimated values, the estimated value of PV surface temperature represented by three coordinate data from the LM-type ANN is shown in the four-dimensional graph in Figure 7. This study chose 14 nodes for better representation. Reducing the number of nodes allowed fewer iterations of the ANN algorithm to provide results in a shorter time.

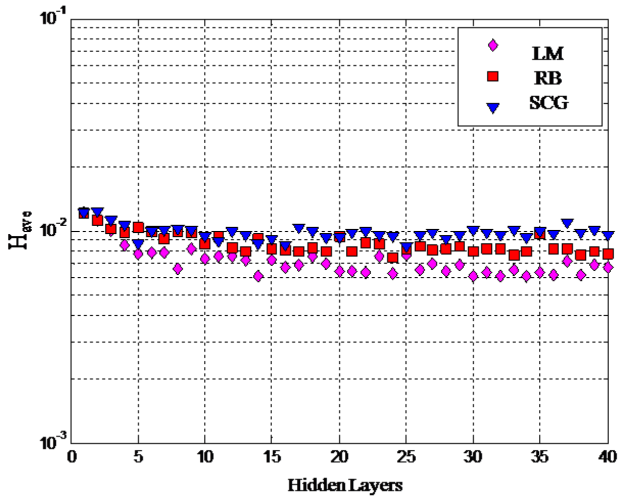

Figure6.Variation results of error rates of hidden node numbers from tests of LM, SCG and RB type ANN models

Table1. Mean error rates for training and test estimations using hidden nodes for LM, SCG and RB

Node number	*LM*	
	Training	*Test*
31	*0.006402*	*0.006364*
32	*0.006141*	*0.006214*
33	*0.006518*	*0.006363*
34*	*0.006146*	*0.005962*
35	*0.006366*	*0.006224*
36	*0.006181*	*0.006071*
37	*0.007161*	*0.007060*
Node number	*SCG*	
	Training	*Test*
21	*0.008042*	*0.007967*
22	*0.008858*	*0.008810*
23	*0.008727*	*0.008673*
24*	*0.007530*	*0.007384*
25	*0.008246*	*0.008141*
26	*0.008472*	*0.008409*
27	*0.008155*	*0.008108*
Node number	*RB*	
	Training	*Test*
13	*0.009533*	*0.009426*
14	*0.00863*	*0.008484*
15	*0.009168*	*0.008973*
16*	*0.008536*	*0.008325*
17	*0.010337*	*0.010082*
18	*0.009985*	*0.009833*
19	*0.009330*	*0.009098*

**Best result*

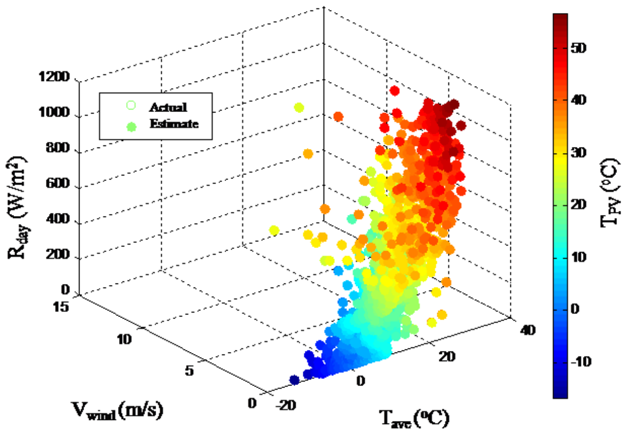

Figure6.Variation results of error rates of hidden node numbers from tests of LM, SCG and RB type ANN models

ii) Using data based on true system data, a new formula to allow estimation of PV module temperature is presented to the literature.

iii) The maximum and mean energy productivity for electricity production of the system on a yearly basis was between 13.135 and 10.67%.

iv) The maximum and mean capacity operating rates of the power station were determined as 86.5% and 31.36%.

It is hoped that the obtained results will be an important resource for academics and those in industry working in this field.

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