Calculation of the cell temperature of a High Concentrator Photovoltaic (HCPV) module: a study and comparison of different methods

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Abstract: Ascertaining the operating cell temperature of a high concentrator photovoltaic (HCPV) module is critical because its electrical parameters are influenced by this factor. However, measuring the cell temperature of an HCPV module is a complex task due to the unique features of such a module. This paper calculates the cell temperature in an HCPV module by using different methods to address this important issue. We conducted a comparative study of four methods used to estimate the cell temperature of an HCPV module, including the IEC 60904-5 method, a method based on thermal resistance proposed by the Instituto de Sistemas Fotovoltaicos de Concentración, the Lineal method and an artificial neural network-based method introduced in this paper. The complete procedures, parameters and coefficients required to estimate the cell temperature with each method are provided. The results show that methods based on direct measurements of the HCPV module perform better than methods based on atmospheric parameters. However, all of the studied methods can be used to estimate cell temperatures with an acceptable margin of error.

Keywords: High concentrator photovoltaic, cell temperature, mathematical methods, outdoor measurements.

1. Introduction

A high concentrator photovoltaic (HCPV) module utilises inexpensive optical devices to concentrate light in a small solar cell, typically a III-V multi-junction (MJ) solar cell [1]. Due to the expected high efficiencies for multi-junction solar cells and HCPV modules, this technology can play an important role in future power generation markets [2, 3].

Multi-junction concentrator solar cells are influenced by their operating temperature. Specifically, the efficiency, maximum power point, open circuit voltage and fill factor of these devices decrease with increased temperatures. In contrast, the temperature influence on the short circuit current of the cells is positive [3-7]. For this reason, the same behaviour is exhibited in HCPV modules [8-9].

Knowing the operating cell temperature of an HCPV module is critical because its electrical parameters are influenced by this factor. However, measuring the cell temperature in an HCPV module is complex due to its unique features [10]. This paper calculates the cell temperature in an HCPV module by using different methods to address this important issue. In particular, four methods of estimating the cell temperature of an HCPV module are described, applied and compared. In addition, the complete procedure used to estimate the cell temperature for each method is provided. The analysed methods are as follows:

- The method described in the international standard IEC 60904-5 [11] that determines the cell temperature of a photovoltaic device from its open circuit voltage.

- The method proposed by the Instituto de Sistemas Fotovoltaicos de Concentración (ISFOC) that determines the cell temperature of an HCPV module from its heat-sink temperature [12].
- The Lineal method proposed in [10] that determines the cell temperature of an HCPV module from atmospheric parameters.
- A new method based on an artificial neural network (ANN) that relates the cell temperature of an HCPV module with atmospheric parameters.

The first two methods are based on direct measurements on the HCPV module, while the Lineal method is based on easily obtained atmospheric parameters. The use of these atmospheric parameters has the advantage of estimating the cell temperature of an HCPV module for a specific location without directly measuring the module. Following this approach, and because ANNs have proven to be very helpful in solving complex problems, a new method based on an artificial neural network is also introduced in this paper to estimate the cell temperature of an HCPV module based on atmospheric parameters.

Section 2 describes the experimental set-up used to perform this study. In Section 3, the methods presented in [10-12] are described and the new ANN-based method is introduced and justified. The necessary parameters and procedures for obtaining the cell temperatures with each are also provided. In Section 4, the results obtained from the cell temperature estimations for each method are presented and a comparative study is performed. The primary conclusions of the study are presented in Section 5.

2. Experimental set-up

The study was conducted at the Centre of Advanced Studies in Energy and Environment (CEAEMA) at the University of Jaen. The major focus of this institution is the outdoor evaluation of HCPV technology [13]. Jaén is located in the south of Spain, which has a continental Mediterranean climate with cold winters, hot summers and a high direct annual irradiation level [14].

The following components were used to carry out this study:

- A two-axis solar tracker designed by BSQ on the roof of the research centre.
- An HCPV module mounted on a two-axis solar tracker. The major characteristics of the HCPV module are shown in Table 1.
- A four-wire electronic load PVPM 1000C40 placed in the laboratory to register the I-V curves.
- A four-wire PT100 placed in contact with the solar cell on a concentrator receiver to measure the cell temperature (T_c) (Figure 1–top right) and a four-wire PT100 placed on the back of the module (under the solar receiver) to measure the heat-sink temperature (T_{h-s}) (Figure 1–bottom right).
- An Agilent 34970A data logger located in the laboratory to record the cell temperature and the heat-sink temperature of the module.
- An atmospheric station (MTD 3000C from GEONICA) to record other outdoor parameters such as direct normal irradiance (DNI), wind speed (W_s) and air temperature (T_{air}). This station is located on the roof of the research centre and is connected through the Ethernet with a PC located in the laboratory.

Figure 1 shows the aforementioned experimental set-up. All of the parameters were recorded every five minutes since January 2011. The module was cleaned once a week and after rainy days to avoid possible electrical losses.

3. Methods for estimating the cell temperature in an HCPV module

In this section, the following methods were considered: the IEC 60904-5 method [11], the method proposed by ISFOC [12] and the Lineal method presented in [10] are described and set. In addition, a new method based on an ANN is introduced and described.

3.1. The IEC 60904-5 Method

The international standard IEC 60904-5 allows the determination of the cell temperature of a photovoltaic device through the open-circuit voltage method. In this study, the method is applied to obtain the solar cell temperature of an HCPV module. The general proposed equation to obtain T_c is:

$$T_c = T_c^* + \beta^{-1}(V_{oc} - V_{oc}^* + (nk(T_c + 273)/q)N_s\ln(DNI^*/DNI) \quad (1)$$

where T_c^* is the cell temperature at the reference conditions, β is the open circuit voltage temperature coefficient (with a value of -25.16 mV/ºC as provided by the manufacturer), V_{oc} is the open circuit voltage of the HCPV module (extracted from the measured I-V curve), V_{oc}^* is the open circuit voltage of the HCPV module under the reference conditions (with a value of 17.82 V as provided by the manufacturer), n is the diode ideality factor of the multi-junction solar cell, k is the Boltzmann constant, q is the electron charge, Ns is the number of solar cells in series, DNI is the measured direct normal irradiance and DNI * is the reference direct normal irradiance. The reference conditions are defined as: $DNI^* = 1000$ W/m^2, $T_c^* =$ 25 ºC and AM1.5d.

In equation (1), the value of n is not known. To estimate this value, equation (1) is rewritten as:

$$(V_{oc} - V_{oc}^*) - \beta(T_c - T_c^*) = n(k(T_c +273)/q)N_s\ln(DNI/DNI^*) \quad (2)$$

where the value of n is empirically obtained by performing a linear regression analysis of $(V_{oc} - V_{oc}^*) - \beta(T_c - T_c^*)$ as a function of $(k(T_c +273)/q)N_s\ln(DNI/DNI^*)$ with a value of n = 3.714. This is consistent with previous studies on the diode ideality factor of MJ solar cells. As seen in [15], where different ideality factors of several MJ solar cells are obtained for cell temperature ranges between 0 and 120 ºC, this parameter is in the range of 3–4.

Once all of the parameters are known, equation (1) must be rewritten as a function of the electrical parameters and direct normal irradiance to estimate the cell temperature of the HCPV module as:

$$T_c = (\beta\, T_c^* + V_{oc} - V_{oc}^* +(nk/q)N_s\ln(DNI^*/DNI)273)/(\, \beta - (nk/q)N_s\ln(DNI^*/DNI)) \quad (3)$$

3.2. Thermal Resistance (ISFOC) Method

The Instituto de Sistemas Fotovoltaicos de Concentración (ISFOC), in cooperation with the Instituto de Energia Solar at the Universidad Politécnica de Madrid (IES-UPM), have developed an outdoor method that addresses the issue of device temperature by taking into account the internal thermal resistance between a solar cell and the back surface of an HCPV module [12, 16]. This method allows for the calculation of the cell temperature from the measurement of the heat-sink module temperature. To apply this method, it is necessary to know the internal thermal resistance (ρ) of the HCPV module, which is defined as the thermal fall between the cell and the heat-sink of the HCPV module as follows:

$$\rho = (T_c - T_{h\text{-}s})/DNI \tag{4}$$

where ρ is empirically obtained by performing a linear regression analysis of ($T_c - T_{h\text{-}s}$) as a function of DNI with a value of $\rho = 0.0104$ K/Wm^{-2}. This parameter is proportional to the thermal resistance (R) between the cell and the heat-sink, but it uses the DNI that falls on the module and not the luminous power that falls on the cell—an easier measurement [16].

A theoretical calculation of the internal thermal resistance of the HCPV module was implemented to verify the obtained value of ρ. In the studied module, the cells have germanium substrates that are bonded onto copper material, which is then bonded onto a heat-sink. Figure 2 shows the structure of the materials between the solar cell and the back surface of the HCPV module and Table 2 shows the heat conductivity (k) and the thickness (L) of each material. Taking into account this structure and the values of k and L for each material, R can be calculated as:

$$R = \Sigma_i (L_i/k_i) \tag{5}$$

where the index i represents each material (germanium, copper and aluminium). Using equation (5) and the data from Table 2, the value of R is obtained as 2.55x10-5 K/Wm^{-2}. To establish a relationship between ρ and R, it is necessary to understand the relationship between the DNI that falls on the module surface and the luminous power received by the cell. The geometric concentration ($C_{geometric}$) of the investigated module is 500x. Taking into account an optical efficiency of approximately 0.85, the optical concentration ($C_{optical}$) is approximately 425x. As a result, the cells in the module receive approximately 425x the DNI that falls on the module. Taking this into account, it is possible to relate ρ and R as follows:

$$\rho = C_{optical}R \tag{6}$$

Using equation (6) and the determined values of $C_{optical}$ and R above, the value of ρ can be theoretically calculated as 0.0108 K/Wm^{-2}. This value is consistent with the empirically obtained value of 0.0104 K/Wm^{-2}. This indicates that the empirical and theoretical procedures used to obtain the internal thermal resistance are valid.

3.3. Linear Coefficients Method

In contrast to the two methods described above, the Lineal method introduced in [10] allows for the calculation of the cell temperature of an HCPV module by using only atmospheric parameters. The aim of the method is to obtain an expression that relates cell temperature with the atmospheric parameters of the specific location of the HCPV module without knowing the internal structure of the module or measuring its electrical parameters. To facilitate its application, the method is based on a simple lineal equation as follows:

$$T_c = T_{air} + aDNI + bW_s \quad (7)$$

The a and b parameters are empirically obtained through a regression analysis of outdoor monitored data with values of a = 0.0611 (ºC/Wm^{-2}) and b = -2.33 (ºC/ms^{-1}), which are similar to the coefficients presented in [10].

3.4. ANN Method

Following the approach of the previous method, a new method for calculating the cell temperature of an HCPV module from easily obtainable atmospheric parameters is introduced in this paper. Because the process of measuring the cell temperature in an HCPV module is complex and because ANNs have been proven effective in solving complex problems [17 – 27], we have developed a method based on the use of an artificial neural network.

3.4.1 Description of the method

The proposed artificial neural network-based method attempts to characterise the relationship between the atmospheric parameters and the cell module temperature. As in the lineal model, the direct normal irradiance (DNI), air temperature (T_{air}), and wind speed (W_s) are used as inputs for the method. The cell temperature can thus be defined as a function of these parameters:

$$T_c = f(DNI, T_{air}, W_s) \quad (8)$$

To estimate this function, a feed-forward neural network trained with the Levenberg-Marquardt back-propagation algorithm has been used. The proposed ANN is synthesised in Figure 3. The number of nodes in the input and the output layers are, respectively, based on the input and output dimensions of the subject under study, while the number of hidden layer nodes is determined empirically. In this case, the input layer has three nodes that correspond to DNI, T_{air}, and W_s, the output layer has one node corresponding to the value of T_c and the hidden layer has five nodes. To determine the best architecture (i.e., the one that best fits the network output to the target), several ANNs with different structures have been trained following the procedure described in 3.4.2.

3.4.2. Training and validation process

To select the best structure of the ANN and to adjust the weights and bias of the hidden and output layers (training process), the ANN requires a set of patterns of how the cell temperature of an HCPV module varies according to atmospheric parameters. To create this set of patterns, the cell temperature and the atmospheric parameters measured using the experimental set-up outlined in Section 2 have been used.

To avoid overfitting during the training process, the available data have been divided into three subsets. The first subset is the *training set* (70% of the sample), which is used for computing the gradient and updating the network weights and biases. The second subset is the *validation set* (15% of the sample), which is used to evaluate the model. The third subset is the *test set* (15% of the sample), which is not used during the training process; it is used to compare the actual and estimated data by the ANN.

During the training process, when an input vector (DNI, T_{air}, W_S) of the *training set* is applied to the network input layer, the network weights and bias are iteratively adjusted using the Levenberg-Markquard algorithm to minimise the mean square error between the network output (T_c measured for this input vector) and the target output (T_c provided by the ANN for this input vector). The Lervenberg-Markquard algorithm updates the ANN weights as follows:

$$\Delta\omega = -\left[\mu I + \sum_{p+1}^{p} J^{p}(\omega)^{T} J^{p}(\omega)\right]^{-1} \nabla E(\omega) \qquad (9)$$

where $J_p(w)$ is the Jacobian matrix of the error vector $E_p(w)$ evaluated in w, and I is the identity matrix. The vector error $E_p(w)$ is the error of the network for a pattern p: $E_p(w) = t_p - y_p(w)$. The parameter l is increased or decreased at each step. If the error is reduced, then l is divided by a factor b; otherwise it is multiplied by b. This calculates the network output, the error vectors, and the Jacobian matrix for each pattern. It then computes Δw using Eq. (9) and recalculates the error, with $w + \Delta w$ as network weights. If the error has decreased, l is divided by b, the new weights are maintained, and the process begins again; otherwise, l is multiplied by b, Δw is calculated with a new value, and it iterates again.

The error on the *validation set* is monitored during the training process. The validation error normally decreases during the initial phase of the training in the same manner as the *training set* error. However, when the network begins to overfit the data, the error on the *validation set* generally begins to rise. When the validation error increases for a specified number of iterations, the training is stopped and the weights and biases at the minimum value of the validation error are returned. The *test set* error is not used during training; it is later used to compare the different models.

The procedure used for designing the ANN can be summarised as follows:

1. Divide the available data into training, validation and test sets.
2. Select the architecture and training parameters.
3. Train the model by using the training set.
4. Evaluate the model by using the validation set.
5. Repeat steps 2-4 using different architectures and training parameters.
6. Select the best model and train it by using data from the training and validation sets.
7. Assess this final model by using the test set.

The final structure of the ANN developed for estimating the cell temperature of the HCPV module from atmospheric parameters is shown in Figure 3. Tables 3 and 4 show the values of the weights and bias for the neurons of the hidden layer and the output layer, respectively, that were obtained for the final model.

To study the behaviour of the ANN developed to calculate the cell temperature, the following statistical parameters have been calculated for different sets of data (training set, validation set and test set): the mean square error (RMSE), the mean bias error (MBE) and the correlation coefficient (R^2), as shown in Table 5. The RSME is lower than 5% for all sets. The MBE is lower than ±0.3%, which indicates that the ANN neither overestimates nor underestimates the cell temperature. The correlation coefficient for all sets varies in the range of 0.94–0.95, which indicates that there is an adequate fit between the actual and predicted data. It is important to note that the *training set* and the *validation set* were used during the training process of the ANN, while the *test set* was comprised of data that the network has never seen. In addition, there is also an adequate fit between the actual and predicted data, in this case an R^2 = 0.95, a MBE = -0.27% and a RSME = 4.73%.

A comparative study of the proposed and previously described methods, as well as a detailed analysis of all the methods for determining the cell temperature of an HCPV module, is implemented in the next section.

4. Comparative study

4.1 Analysis of results

First, to analyse the results in the estimation of the cell temperature with the four methods described above, a linear regression analysis between the actual and predicted data was performed, as shown in Figure 4. Based on this analysis, the method that yields the best results is the ISFOC method, with a R^2 = 0.99. The IEC method provides similar results to the ISFOC, with a R^2 = 0.98. The Lineal method shows the poorest results, with a R^2 = 0.90. The proposed method based on an ANN improves on the Lineal method but falls short of the IEC and ISFOC methods, with a R^2 = 0.95. Based on this analysis, it can be concluded that all of the methods present a good match between the actual and predicted data because their R^2 values are equal to or greater than 0.90.

In addition to the linear regression analysis, the MBE and RMSE (relative and absolute values) between the actual and predicted data have also been calculated to study the results of the used methods in more detail, as shown in Table 6. The MBE for the four studied methods is approximately 0%, which indicates that the methods neither overestimate nor underestimate the cell temperature. With regard to the RMSE, the ISFOC method shows the best results, with a relative RMSE = 2.47% and an absolute RMSE = 1.70 ºC. Similar results are obtained with the IEC method, showing a relative RMSE = 2.95% and an absolute RMSE = 2.00 ºC. As in the previous analysis, the Lineal method provided the poorest results, with an RMSE = 6.40% and an absolute RMSE = 4.30 ºC. The proposed method improves on the Lineal method but falls short of the other two methods, with a RMSE = 4.80% and an absolute RMSE = 3.24 ºC. Based on this analysis, it can also be concluded that the four methods perform effectively in the prediction of the cell temperature of an HCPV module. The four methods have a MBE almost equal to 0% and a maximum absolute RMSE lower than 4.30 ºC an acceptable margin of error, taking into account that cells in an HCPV module are working in the range of 50 – 80 ºC in 80% of the cases. The distribution of the cell temperature measured during the experiment is shown in Figure 5. This distribution is consistent with the average working cell temperature of an HCPV module as noted by different authors and research groups [28, 29].

Based on the analysis of R^2, MBE and RMSE between the actual and estimated data, it can be stated that the four methods can be used to estimate the cell temperature of an HCPV with sufficient accuracy. However, as seen in Figure 4, some of the methods show a significant range of scatter between the actual and predicted data. To study this scatter in more detail, the absolute RMSE for each cell temperature for the studied methods has been calculated and shown in Figure 6. The ISFOC method again shows the best results, with a performance that is almost constant for all working cell temperatures with absolute RMSE values varying from 3.0 ºC to 1.0 ºC. The IEC method shows similar results to the ISFOC method for cell temperatures above 30 ºC; however, for cell temperatures below 30 ºC the absolute RMSE shows a tendency to increase as the cell temperature decreases. This method shows the widest range of scatter, with absolute RMSE values varying from 7.5 ºC to 1.0 ºC. The Lineal method shows the highest values of absolute RMSE for each cell temperature, ranging from 7.0 ºC to 3.2 ºC and without showing any particular trend. As for the ANN method, the absolute RMSE is centred around 3.0 ºC for all cell temperatures, although it shows a tendency to increase at the highest cell temperatures. The highest absolute RMSE values for all methods occur for temperatures lower than 30 ºC or higher than 80 ºC. However, as previously noted, the working cell temperature of an HCPV module is in the range of 50 – 80 ºC in approximately 80% of the cases. This indicates that, despite the fact that some methods provide better results than others, all of them can be used to estimate the cell temperature of an HCPV module with sufficient accuracy.

4.2. Study of the influence of the errors in the cell temperature estimation in the calculation of the maximum power of an HCPV module

Knowledge of the cell temperature is an important issue in estimating the electrical parameters of an HCPV module. The maximum power (P) can be considered the most important because it discloses the energy production of an HCPV system. Because of this, most of the models for the electrical characterisation of HCPV modules only address the estimation of the maximum power [30]. To account for this, we studied the influence of the errors in the estimation of the cell temperature in the calculation of the maximum power of an HCPV module.

The maximum power of an HCPV device can be expressed as:

$$P = P^{*}(DNI/DNI^{*})(1 - \delta(T_c^{*} - T_c)) \qquad (10)$$

where P^{*} is the maximum power at the reference conditions and δ is the temperature coefficient of the maximum power.

The deviation (ΔP) between the maximum power calculated with the actual cell temperature and the maximum power calculated with the estimated cell temperature using the studied methods can be expressed as:

$$\Delta P\ (\%) = (1 - P(T_{c,actual})/\ P(T_{c,estimated}))100 \qquad (11)$$

Taking into account equations (10) and (11), ΔP (%) can be expressed as:

$$\Delta P\ (\%) = [(1 - \delta(T_c^{*} - T_{c,actual}))/\ (1 - \delta(T_c^{*} - T_{c,estimated}))]100 \qquad (12)$$

To estimate ΔP (%) by using equation (12), it is necessary to know the value of δ. The temperature dependence of several HCPV modules has been reported in [8]. Based on this study, a value of δ = -0.20%/K has been selected as a representative value of an HCPV module.

The histogram of the distribution of ΔP (%) for the studied methods is shown in Figure 7. The ISFOC method shows the best results, with a maximum deviation in the calculation of maximum power of ±1.0% and a deviation of ±0.5% in 90% of the cases. The IEC method shows the second best results, with a deviation ranging from -3.5% to 2.0%, although 85% of the cases are in the range of ±0.5%. The Lineal method yields the poorest results, with a maximum deviation of ±4.5%, although it is in the range of ±1.0% in 72% of the cases and in the range of ±1.5% in 88% of the cases. As for the proposed method based on ANN, the maximum deviation is in the range of ±2.5% although it is in the range of ± 0.5% in 62% of the cases and in the range of ±1.0% in 86% of the cases. Once again, the proposed method improves on the results obtained through the Lineal method but falls short of the others. Based on this analysis, it can be seen that the deviation in the estimation of the maximum power introduced by the methods is in the range of ±1.5% in the majority of the cases, which indicates that all of the methods can be used to estimate the cell temperature of an HCPV module with a satisfactory degree of accuracy in order to estimate the maximum power.

5. Conclusions

This paper has examined four methods for estimating the cell temperature of an HCPV module. The studied methods were the IEC 60904-5 method, the ISFOC method, the Lineal method and a method based on artificial neural networks introduced in this paper. The complete procedures, parameters are coefficients required to estimate the cell temperature with each of these methods was also provided.

To compare and analyse the results of these methods, a number of statistical analyses were conducted. Based on these analyses, it can be concluded that the ISFOC method shows the best results with a R^2 = 0.99, a relative RMSE = 2.47% and an absolute RMSE = 1.70 ºC. The IEC method shows similar results, with a R^2 = 0.98, a relative RMSE = 2.95% and an absolute RMSE = 2.00 ºC. The Lineal method provides the poorest results, with a R^2 = 0.90, a relative RMSE = 6.40% and an absolute RMSE = 4.30 ºC. Finally, the proposed method based on an ANN significantly improves on the results of the Lineal method but falls short of the other two, with a R^2 = 0.95, a relative RMSE = 4.80% and an absolute RMSE = 3.24 ºC. In addition, the absolute RMSE for each cell temperature was calculated for a more detailed analysis of the scatter in some of the methods. Taking into account that the working cell temperature of an HCPV module is in the range of 50 – 80 ºC in 80% of the cases, this analysis leads to the same conclusions mentioned above: the ISFOC and IEC methods show the best results, the Lineal method provides the poorest results, and the ANN method improves on the results of the Lineal method but not the other two. The four methods show a MBE of near 0%, indicating that none of them overestimate or underestimate the cell temperature.

A study on the influence of the errors in the estimation of the cell temperature in the calculation of the maximum power of an HCPV module was also implemented. In particular, the deviation between the maximum power calculated with the actual cell temperature and the maximum power calculated with the estimated cell temperature using the studied methods was analysed. Based on this analysis, it can be concluded that the ISFOC method shows the best results, with a deviation of ±0.5% in 90% of the cases, the IEC method shows the second best results, with a deviation of ±0.5% in 85% of the cases and the Lineal method presents the poorest results, with a deviation of ±1.5% in 88% of the cases. The proposed method improves on the results of the Lineal method, with a deviation of ±1.0% in 86% of the cases, but provides worse results than the other two methods.

It is important to note that, despite the fact that some methods perform more efficiently than others, all of them could be used for the estimation of the cell temperature with an acceptable degree of accuracy. This is because all of them have an R^2 value equal to or greater than 0.90, an absolute RMSE lower than 4.30 ºC (considered an acceptable degree of error, taking into account that the cells in an HCPV module work in the range 50 – 80 ºC in approximately 80% of the cases), a MBE near 0% and a deviation in the estimation of the maximum power in the range of ±1.5% in the majority of the cases.

It can also be concluded that the methods based on direct measurements of an HCPV module (such as heat-sink temperature or open circuit voltage) provide better results than methods based on atmospheric parameters. Despite this, it is important to note that the methods based on atmospheric parameters have the advantage of allowing the estimation of the cell temperature of an HCPV module for a specific location without directly measuring the module. Taking this into account, the proposed method based on artificial neural networks significantly improves upon the Lineal method and can be considered a useful new tool for estimating the cell temperature of an HCPV module.

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Figure caption

Figure 1. Experimental set-up used to carry out the study at the Centre of Advanced Studies in Energy and Environment of the University of Jaén.
Figure 2. Structure of materials between the solar cell and the back surface of the HCPV studied module.
Figure 3. Final structure of the proposed artificial neural network to estimate the cell temperature of a HCPV module from atmospheric parameters.
Figure 4. Linear regression analysis between actual and predicted data using the four studied methods.
Figure 5. Distribution of cell temperature of the HCPV module measured during the experiment.
Figure 6. Absolute root mean square for each cell temperature for the four studied methods.
Figure 7. Histogram of the distribution of ΔP (%) for the studied methods.