Lecture Notes in Artificial Intelligence 9648

Subseries of Lecture Notes in Computer Science

LNAI Series Editors

Randy Goebel
University of Alberta, Edmonton, Canada
Yuzuru Tanaka
Hokkaido University, Sapporo, Japan
Wolfgang Wahlster
DFKI and Saarland University, Saarbrücken, Germany

LNAI Founding Series Editor

Joerg Siekmann
DFKI and Saarland University, Saarbrücken, Germany

Francisco Martínez-Álvarez · Alicia Troncoso
Héctor Quintián · Emilio Corchado (Eds.)

Hybrid Artificial Intelligent Systems

11th International Conference, HAIS 2016
Seville, Spain, April 18–20, 2016
Proceedings

Springer

Editors
Francisco Martínez-Álvarez
Universidad Pablo de Olavide
Sevilla
Spain

Alicia Troncoso
Universidad Pablo de Olavide
Sevilla
Spain

Héctor Quintián
University of Salamanca
Salamanca
Spain

Emilio Corchado
University of Salamanca
Salamanca
Spain

ISSN 0302-9743 ISSN 1611-3349 (electronic)
Lecture Notes in Artificial Intelligence
ISBN 978-3-319-32033-5 ISBN 978-3-319-32034-2 (eBook)
DOI 10.1007/978-3-319-32034-2

Library of Congress Control Number: 2016934675

LNCS Sublibrary: SL7 – Artificial Intelligence

© Springer International Publishing Switzerland 2016
This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.
The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.
The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, express or implied, with respect to the material contained herein or for any errors or omissions that may have been made.

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer International Publishing AG Switzerland

Estimating the Maximum Power Delivered by Concentrating Photovoltaics Technology Through Atmospheric Conditions Using a Differential Evolution Approach

Cristobal J. Carmona[1(✉)], F. Pulgar[2], Antonio Jesús Rivera-Rivas[2], Maria Jose del Jesus[2], and J. Aguilera[3]

[1] Department of Civil Engineering, University of Burgos, 09006 Burgos, Spain
cjcarmona@ubu.es
[2] Department of Computer Science, University of Jaén, 23071 Jaén, Spain
{fpulgar,arivera,mjjesus}@ujaen.es
[3] Department of Electronics and Automatization Engineering, University of Jaén, 23071 Jaén, Spain
aguilera@ujaen.es

Abstract. The Concentrating Photovoltaic technology is focused on the generation of electricity reducing the associated costs. The main characteristics is to concentrate the sunlight in solar cells by means of optical device such as plastic or glass material. This technology could contribute with several benefits to our environmental. This paper presents a new study of the Concentrating Photovoltaic technology with the analysis of the solar spectrum considering the impact of the direct normal irrandiance spectral distribution. In this way, a estimation of regression coefficients for the spectral matching ratio multivariable regression and the average photon energy multivarible regression are obtained through a differential evolution approach. The accurate calculation of the model parameters reveals relations among the atmospheric conditions very useful for the experts.

Keywords: Regression solar · Data mining · Differential evolution · Concentrating Photovoltaic technology

1 Introduction

The main aim of Concentrating Photovoltaic (CPV) technology is to generate electricity with a lower associated cost. Regarding this purpose, the sunlight is concentrated in the solar cell by means of an optical device, deriving in an increase of the cell efficiency and a resulting reduction of the required cell area to generate the same power. These optical devices are commonly made of plastic or glass material, which are significantly cheaper than the solar cells. CPV modules are, in most of the cases, based on Multijunction (MJ) solar cells, which moreover tend to be composed of a serial layout of high efficiency semiconductor

© Springer International Publishing Switzerland 2016
F. Martínez-Álvarez et al. (Eds.): HAIS 2016, LNAI 9648, pp. 273–282, 2016.
DOI: 10.1007/978-3-319-32034-2_23

materials [13]. This technology has numerous benefits like higher energy density, higher efficiency, needs of lower surface and lower semiconductor material requirements [5]. Nevertheless, some technical and economic barriers must be removed to reduce the electricity production costs using this technology and to make it really competitive.

Because the bankability of a CPV Plant is an important topic to pave the way toward a sustained growth of this technology and this bankability is based on energy yield prediction under real atmospheric conditions, an accurate estimate of the maximum power (P_M) of the CPV modules is crucial [9,14]. The accurate calculation of this P_M would allow to estimate the electric production of a CPV power plant and the analysis of its costs and profitability, with the consequent benefits for the commercial development of this CPV technology. The calculation of the P_M delivered by a CPV module under specific environmental parameters is not a trivial issue. A generalized problem which concerns to the lack of an international standard method for outdoor power rating of CPV modules, is perceived by investors as a worrying item. The American Society for Testing and Materials (ASTM) E2527-06 is, until now, the unique standard which allows calculating the maximum power delivered by a CPV module under specific atmospheric conditions. However, this standard does not consider the spectral distribution as one of these input environmental conditions. As it has been previously studied by several researchers the spectral distribution of the direct normal irradiance has an important effect on the electrical behaviour of CPV modules. Due to the latter, its inclusion in the modelling has a paramount relevance. In this work, two different variables have been used to include this spectral influence: the Spectral Machine Radio (SMR) and the Average Photon Energy (APE).

This work proposes the use of two different equations for SMR and APE. The first equation must be implemented when the DNI spectral distribution has a higher red-content than the standard one; otherwise, the second equation will be used when the incident direct spectrum has a higher blue-content than the standard. This estimation model is, at the same time and with the objective of increasing its accuracy, divided into two different spectrum intervals. The optimisation of these equations is analysed through different proposals such as differential evolution (DE), support vector machine (SVM), artificial neural networks, etc. Results obtained in the experimental study show a good behaviour of the DE algorithm in order to model through multiple linear equations the P_M, as a function of the following atmospheric conditions: DNI, T_A, W_S, and DNI spectral distribution through two alternative indexes: SMR and APE. The regression coefficients with the best fir to the equations are obtained through the algorithm with the lowest error in the prediction of the P_M.

The contribution is organized as follows: Sect. 2 describes the main properties of CPV technology analysing the influential atmospheric conditions in order to measure the electric performance of the CPV modules, and the use of two indexes to define the influence of DNI spectral distribution on the CPV modules' electrical performance. Section 3 outlines the experimental framework and shows the results obtained, and finally, some concluding remarks are outlined.

2 CPV Technology

The main aim of the CPV technology is to contribute to the generation of electricity with a lower cost, by using the least possible amount of material. Most of CPV modules available in the market use high efficient MJ solar cells, with an optical device to focus the solar radiation in the MJ solar cell surface. The required optical device must include a primary optics, that is in charge of collecting and concentrating the *DNI*, and a secondary optics to uniformly distribute the sunlight from the primary optic, along the whole surface of the solar cell [11]. Due to the latter, only the direct component of the global radiation is used, in other words, the diffuse component is not exploited. The assembly of various solar cells, with their respective complementary elements, constitutes a CPV module. Finally, it is necessary to use a tracking system to hold the CPV module and to orient it towards the Sun, in such way that the component solar cells are, at every moment, perpendicularly disposed to the solar ray [16].

2.1 Study of Influential Atmospheric Conditions on the Electric Performance of CPV Modules

The *DNI* is considered as the main atmospheric parameter which influences the outdoor electric performance of a CPV module. The relation between DNI and P_M is almost linear, so its effect is predominant.

Using the DNI as the integration value along the whole wavelength range for a specific photovoltaic (PV) device is a common practice. Nevertheless, we can consider the DNI value for each wavelength value, obtaining the *solar spectrum distribution*. As has been widely demonstrated, the DNI, as well as its spectral distribution, have an important influence on the electric performance of MJ solar cells. It is well known that the MJ solar cells temperature affect to their electric performance. In this sense, the temperature has an almost negligible positive effect on the short circuit current delivered by the MJ solar cell, and a negative predominant effect on both the open circuit voltage and P_M [10,12,19,23]. The same behaviour is observed when analyzing the impact of the temperature on the electric performance of CPV modules equipped with MJ solar cells [21]. However, the own disposition of the MJ solar cells inside the CPV module makes it very difficult to measure their temperature. In this work, T_A is considered as influential factor, given a direct relation between cell temperature and T_A [1,2].

The consideration of the W_S as one of the influential factors whose contribution must be added in the equation proposed by the ASTM E-2527-09 standard. In this way, W_S can perform a positive refrigerating effect on the electric performance of a CPV system, cooling the MJ solar cells which compose the module down, and obtaining therefore a better behaviour [4]. However, high W_S values can also exert a negative effect of misalignment on the tracker [15], displacing the MJ solar cells from their optimum arrangement in the solar beam direct trajectory.

A review of the main models for estimating the P_M of CPV modules has been recently published [22]. However, it must be taken into account that, when talking about standard power rating methods, the ASTM E2527-09 methodology is the unique model in CPV field.

2.2 The Use of *SMR* and *APE* Indexes to Characterise the *DNI* Spectral Distribution

The influence of the solar spectrum distribution on the electric performance of CPV modules can be considered from two different indexes: *SMR* and *APE*. On the one hand, *SMR* is defined as a index which expresses the ratio between the effective *DNI* received by two different junctions (top and middle) of the MJ solar cells which compose the CPV module [6]. When the incident solar spectrum differs from the AM 1.5D standard, the effective *DNI* collected by each of these junctions could be different, so the photocurrent generated by the whole MJ solar cell is limited by the junction generating a lower photocurrent at each moment. The *SMR* index is calculated as follows:

$$SMR\,(AM1.5D)^{TOP-junction}_{MIDDLE-junction} = \frac{DNI_{TOP-junction}}{DNI_{MIDDLE-junction}} \tag{1}$$

where $DNI_{TOP-juntion}$ and $DNI_{MIDDLE-junction}$ represent the effective *DNI* collected by the top and middle junction, respectively. Attending to the last equation, there are three different possibilities:

- $SMR < 1$, the incident spectral distribution is red-richer than the standard one, which means that the middle junction collected an effective *DNI* higher than the one collected by the top junction, being this last the limiting junction.
- $SMR > 1$, the incident spectral distribution is blue-richer than the standard one, which means that the top junction collected an effective *DNI* higher than the one collected by the middle junction, being this last the limiting junction.
- $SMR = 1$, top and middle junctions collected the same effective *DNI*, which means that the incident spectrum coincides with the AM1.5D standard one.

The *SMR* influence on the normalized Short Circuit Current (ISC_N) -and therefore on the P_M- generated by a CPV module were normalized in terms of *DNI*, to avoid its predominant effect. As can be appreciated, under *SMR* values lower than 1, this factor has a positive influence on the electric performance of the CPV module. In other words, increasing values of *SMR* makes the module to produce a higher ISC_N. Otherwise, when *SMR* values are close to 1 (which means spectral distributions close to the AM1.5D standard one), the module is working in an optimum way. Under *SMR* values higher than 1, this parameter has a negative influence, making the module to deliver a lower value of ISC_N.

On the other hand, *APE* index is defined as a unique value which characterises the shape of the *DNI* spectral distribution between a determined wavelength range [17]. As increasing the value of the *APE* index, the incident spectrum is expected to have a higher blue content. The *APE* index can be obtained by calculating the following equation:

$$\frac{\int_a^b E_\lambda(\lambda)d\lambda}{\int_a^b \phi_\lambda(\lambda)d\lambda} \tag{2}$$

where:

- E_λ $(W\,(m^2 \cdot nm))$: Spectral irradiance.
- ϕ $(1/(m^2 \cdot nm \cdot s))$: Spectral photon flux density (ratio between the spectral irradiance E_λ and the energy of the photon of wavelength $lambda$).
- a and b are considered as the integration limits and depend on the spectroradiometer specifications.

The APE index has been introduced as a remarkable parameter to describe, in an easy way, the impact of the solar spectrum change in different PV solar technologies [20].

There is an intrinsic relation between APE and SMR which is almost linear, except when the solar spectral distribution has high red-content, in which APE values are lower than expected. In this way, it is possible to obtain a first degree polynomial expression to define this relation, without entailing a big error:

$$f(x) = p_1 x + p_2 \tag{3}$$

Coefficients (with 95 % of confidence bounds):

- $p_1 = 0.34\,(0.3385, 0.3414)$
- $p_2 = 1.487\,(1.485, 1.488)$

Goodness of fit (values given by $Matlab_{TM}$ curve fitting toolbox):

- $R - square : 0.9601$
- $RMSE : 0.00644$

From the last obtained equation, it is possible to calculate the APE value which corresponds to the AM1.5D standard spectral distribution, or in other words, the APE value which corresponds to $SMR = 1$. As can be observed, the maximum of the function was found for SMR values closer to the unit, under which the CPV module should work on its optimum manner. Because of that, $SMR = 1$, that according to the linear relation between SMR and APE corresponds to $APE = 1.83$, is going to be considered as the turning point to the definition of the model proposed in this paper, dividing it into two different spectral intervals. This turning point corresponds to the AM 1.5D standard spectral distribution.

3 Experimental Study

The data were obtained from one model of CPV modules, whose main characteristics are solar cells type $Multijunction - GaInP/Ga(In)As/Ge$ with 25 solar cells and a concentration factor of 550. The measures were acquired at the rooftop of the Higher Polytechnical School of Jaén during the period between March 2013 and November 2013, forming a whole dataset composed of 8780 samples in the case of the module $M1$. The atmospheric measures were registered every 5 min using the outdoor devices specified in Table 1 and described below:

Table 1. Measurement of atmospheric conditions by outdoor devices.

Atmospheric condition	*Units*	*Outdoor device*	*Measures range*
DNI	(W/m^2)	*Pyheliometer*	[140–1024]
Spectrum APE	(eV)	*Spectro – radiometer*	[1.59–1.87]
Spectrum SMR	$(-)$	*Spectro – heliometer*	[0.40–1.13]
T_A	$(°C)$	*Spectro – heliometer*	[11.39–41.82]
W_S	(m/s)	*Anemometer*	[0.04–20.50]

- A Kipp & Zonnen^{TM} CHP 1 pyrheliometer to the measurement of the direct normal irradiance (DNI).
- An EKO^{TM} MS700 spectro-radiometer with a collimator tube to the measurement of the direct normal spectral Irradiance distribution with a wavelength range of 350–1050 nm. From the measurement of the spectrum distribution the APE value is calculated.
- A Triband spectro-heliometer composed by three component cells, with the same structure of the MJ solar cells which compose the analysed CPV modules. In this way it is possible to independently measure the effective irradiance collected by each junction, and so calculate the SMR index.
- A meteorological Station formed by a Young^{TM} 41382VC relative humidity & temperature probe to register the T_A and a Young^{TM} 05305VM anemometer to measure the W_S.

The analysis of the data is performed in two stages. Firstly, an experimental study with different algorithms is performed in order to measure the mean squared error (MSE) of the P_M for the module, i.e. the MSE between real P_M values and P_M values predicted. Next, the regression coefficients obtained for the approach with the best results and more interpretable are presented. Algorithms included in the experimental study are outlined below:

- The DE algorithm is a stochastic algorithm for optimising and searching based on the natural evolution process and it was defined by Storn and Price [24] as a versatile function optimiser where mutation is emphasised. DE uses a mutation operator to promote the diversity in the population where a scaled difference between an original individual and several randomly selected individuals from the same population is performed. Subsequently to the result a recombination operator is applied in order to lead the search for an optimal solution.
- A multiple linear regression (MLR) method based on [8] where the most popular estimation method for the coefficients, least squares, pick them to minimize the residual sum of squares.
- Wang and Mendel (WM) [25] is a method for generating fuzzy rules by supervised learning. This fuzzy classical approach divides the input and fuzzy spaces of the given numerical data into fuzzy regions and generates a linguistic fuzzy rule for each fuzzy region (if it is possible) from the given data. The fuzzy rule

based system uses the t-norm product and centroid defuzzification formula to determine the output

- Classification and regression trees ($CART$) [3] is a kind of decision tree that can produce either classification or regression trees, depending on the given output variable. This decision tree is composed of: Rules for splitting data at a tree node based on the values of the input variables; Stopping rules for stablishing when a branch is terminal; an output value for the dependent variable in each terminal node.
- The SVM model uses the sequential minimal optimization training algorithm and treats a given problem in terms of solving a quadratic optimization problem. The $NUSVR$ [7], also called $vSVM$, for regression problems is an extension of the traditional SVM and it aims to build a loss function.
- $MLPConjGrad$ [18] uses the conjugate gradient algorithm to adjust weight values of a multilayer perceptron. Compared to gradient descent, the conjugate gradient algorithm takes a more direct path to the optimal set of weight values. Usually, the conjugate gradient is significantly faster and more robust than the gradient descent. The conjugate gradient also does not require the user to specify learning rate and momentum parameters.

It is important to separate with respect to the interpretability of the algorithms in order to analyse the possibility to know the regression coefficients in the P_M equations. In this way, we could divide algorithms in two groups: Interpretable (DE, MLR, WM and $CART$) and non-interpretable ($NUSVR$ and $MLPConjGrad$). Finally, it is important to remark that the experimentation process is performed through a separation between training and test dataset. In this case, we use 80 % (training) of the whole dataset to calculate the regression coefficients that best fit the equations which compose the proposed model. Otherwise, 20 % (test) of the whole dataset was used to validate the predictive capacity of the proposed model.

Table 2. MSE test results obtained to the CPV module under study

Index	Interpretable models				Non interpretable	
	DE	MLR	WM	CART	NUSVR	MLPConjGrad
$SMR < 1$	**8.35**	9.31	16.83	8.36	8.80	**5.34**
$SMR \geq 1$	**7.47**	7.58	32.92	8.25	7.99	**7.23**
$APE < 1.83$	**8.41**	9.45	20.08	8.59	11.27	**6.24**
$APE \geq 1.83$	**6.79**	6.90	37.37	8.21	7.24	**6.55**

The MSE are shown in Table 2. The algorithm with the best results is the $MLPConjGrad$. However, it is impossible to analyse the regression coefficients with this algorithm because they are considered “black box” and it is very difficult to show relations, coefficients, impact and so on between the variables. In this way, the following algorithm with best results is the DE. This approach is interpretable and these results show the capacity to solve the proposed multiple linear regression model with MSE values within the interval [6.79–8.41]. In Table 3, the regression coefficients obtained by the DE algorithm for the analysed CPV module are presented.

Table 3. Regression coefficients obtained by DE methodology for the CPV modules

Index	a_1	a_2	a_3	a_4	a_5
$SMR < 1$	0.076423	−1.63E-05	−1.11E-04	3.00E-04	0.062229
$SMR \geq 1$	0.150911	−9.48E-06	−3.63E-04	3.38E-04	−0.012287
$APE < 1.83$	−0.178408	−1.66E-05	−1.53E-04	3.01E-04	0.174229
$APE \geq 1.83$	0.219101	−8.79E-06	−3.75E-04	3.06E-04	−0.044181

According to the regression coefficients calculated by the DE-proposal for the module, it can be remarked:

- Almost linear relation between DNI and P_M delivered by CPV modules. This can be appreciated due to the low values of a_2 coefficients compared to a_1 ones.
- Very slight negative influence of T_A on the P_M delivered by CPV modules. This influence is given by a_3 regression coefficients.
- Very slight positive influence of W_S on the P_M delivered by CPV modules. This influence is given by a_4 regression coefficients.
- As it was predicted, a positive influence of the DNI spectral distribution on the P_M of the CPV modules for values of $SMR < 1$ or $APE < 1.83$ is observed: when increasing the value of SMR or APE, the P_M is increased. This influence is given by a_5 regression coefficients for the first spectral interval.
- Negative influence of the DNI spectral distribution on the P_M of the CPV modules for values of $SMR \geq 1$ or $APE \geq 1.83$. In this way, when increasing the value of SMR or APE, the P_M is decreased. This effect is perceptible through the analysis of a_5 regression coefficients for the second spectral interval.

The multivariable regression model presented in this paper is very important as it allows obtaining the regression coefficient which quantify the influence of different atmospheric conditions on the P_M delivered by a CPV module. This functionally can not be achieved by an ANN model.

4 Conclusions

The multivariable regression model proposed in this work is based on the ASTM E-2527-09. This standard defines a methodology to calculate the P_M delivered by CPV modules or systems, through the resolution of a multiple linear equation based on the following input atmospheric conditions: DNI, T_A and W_S.

To calculate this P_M value, the regression coefficients which compose the multiple linear equation must be previously calculated. Nevertheless, the methodology proposed by the ASTM E-2527-09 has a big drawback, as it does not consider the influence of the solar spectrum distribution. In this work, the standard methodology has been modified in order to make it more accurate. This modification consists on adding an additional term which quantifies the influence of the DNI spectral distribution on the P_M delivered by CPV modules. The proposed model allows to consider this additional term through the use of two alternative indexes: SMR and APE. In this way, the applicability of the model is increased as it can be implemented from the measurement acquired through a triband spectro-heliometer (SMR) or a spectro-radiometer(APE).

The P_M values obtained by the model (through the regression coefficients calculated by means of DE) under determined atmospheric conditions, were compared with the corresponding real P_M values for one analysed CPV modules. As a result, it is concluded that the proposed model obtained good MSE values within of a considerable range of powerful lower than 3 %. Specifically, In PV field, errors between [0–2]% are classified as a very good predictions, in the interval between [2–3.5]% as good, and within the range [3.5–5]% they are considered as satisfying.

Acknowledgments. This work was supported by the Spanish Science and Innovation Department under project ENE2009-08302, by the Department of Science and Innovation of the Regional Government of Andalucia under project P09-TEP-5045, and by Spanish Ministry of Economy and Competitiveness under project TIN2015-68454-R (FEDER Founds).

References

1. Almonacid, F., Pérez-Higueras, P., Fernández, E., Rodrigo, P.: Relation between the cell temperature of a hcpv module and atmospheric parameters. Solar Energy Mater. Solar Cells **105**, 322–327 (2012)
2. Antón, I., Martínez, M., Rubio, F., Núñez, R., Herrero, R., Domínguez, C., Victoria, M., Askins, S., Sala, G.: Power rating of cpv systems based on spectrally corrected dni, vol. 1477, pp. 331–335 (2012)
3. Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J.: Classification and Regression Trees. Chapman & Hall, New York (1984)
4. Castro, M., Domínguez, C., Núez, R., Antón, I., Sala, G., Araki, K.: Detailed effects of wind on the field performance of a 50 kw cpv demonstration plant. In: AIP Conference Proceedings, vol. 1556, pp. 256–260 (2013)
5. Chan, N., Brindley, H., Ekins-Daukes, N.: Impact of individual atmospheric parameters on cpv system power, energy yield and cost of energy. Prog. Photovoltaics **22**, 1080–1095 (2014)
6. C. Domínguez, I. Askins, S. Antón, and G. Sala. Indoor characterization of cpv modules using helios 3198 solar simulator. In: 24th European Photovoltaic Solar Energy Conference and Exhibition, pp. 165–169 (2009)
7. Fan, R., Chen, P., Lin, C.: Working set selection using the second order information for training svm. J. Mach. Learn. Res. **6**, 1889–1918 (2005)

8. Flury, B., Riedwyl, H.: Multiple linear regression. In: Multivariate Statistics, pp. 54–74 (1988)
9. Gupta, R.: CPV: expansion and bankability required. Renew. Energy focus **14**(4), 12–13 (2013)
10. Helmers, H., Schachtner, M., Bett, A.: Influence of temperature and irradiance on triple-junction solar subcells. Solar Energy Mater. Solar Cells **116**, 144–152 (2013)
11. Herrero, R., Victoria, M., Domínguez, C., Askins, S., Antón, I., Sala, G.: Concentration photovoltaic optical system irradiance distribution measurements and its effect on multi-junction solar cells. Prog. Photovoltaics Res. Appl. **20**(4), 423–430 (2012)
12. Kinsey, G., Hebert, P., Barbour, K., Krut, D., Cotal, H., Sherif, R.: Concentrator multijunction solar cell characteristics under variable intensity and temperature. Prog. Photovoltaics Res. Appl. **16**(6), 503–508 (2008)
13. Law, D., King, R., Yoon, H., Archer, M., Boca, A., Fetzer, C., Mesropian, S., Isshiki, T., Haddad, M., Edmondson, K., Bhusari, D., Yen, J., Sherif, R., Atwater, H., Karam, N.: Future technology pathways of terrestrial iii-v multijunction solar cells for concentrator photovoltaic systems. Solar Energy Mater. Solar Cells **94**(8), 1314–1318 (2010)
14. Leloux, J., Lorenzo, E., Garca-Domingo, B., Gueymard, J.A.C.: A bankable method of assessing the performance of a cpv plant. Appl. Energy **118**(C), 1–11 (2014)
15. Lin, C.-K., Fang, J.-Y.: Analysis of structural deformation and concentrator misalignment in a roll-tilt solar tracker. In: AIP Conference Proceedings, vol. 1556, pp. 210–213 (2013)
16. Luque, A., Sala, G., Luque-Heredia, I.: Photovoltaic concentration at the onset of its commercial deployment. Prog. Photovoltaics Res. Appl. **14**(5), 413–428 (2006)
17. Minemoto, T., Nakada, Y., Takahashi, H., Takakura, H.: Uniqueness verification of solar spectrum index of average photon energy for evaluating outdoor performance of photovoltaic modules. Solar Energy **83**(8), 1294–1299 (2009)
18. Moller, M.F.: A scaled conjugate gradient algorithm for fast supervised learning. Neural Netw. **6**(4), 525–533 (1993)
19. Nishioka, K., Takamoto, T., Agui, T., Kaneiwa, M., Uraoka, Y., Fuyuki, T.: Annual output estimation of concentrator photovoltaic systems using high-efficiency ingap/ingaas/ge triple-junction solar cells based on experimental solar cell's characteristics and field-test meteorological data. Solar Energy Mater. Solar Cells **90**(1), 57–67 (2006)
20. Nofuentes, G., García-Domingo, B., Muoz, J., Chenlo, F.: Analysis of the dependence of the spectral factor of some pv technologies on the solar spectrum distribution. Appl. Energy **113**, 302–309 (2014)
21. Peharz, G., Ferrer Rodríguez, J., Siefer, G., Bett, A.: Investigations on the temperature dependence of cpv modules equipped with triple-junction solar cells. Prog. Photovoltaics Res. Appl. **19**(1), 54–60 (2011)
22. Rodrigo, P., Fernández, E., Almonacid, F., Pérez-Higueras, P.: Models for the electrical characterization of high concentration photovoltaic cells and modules: a review. Renew. Sustain. Energy Rev. **26**, 752–760 (2013)
23. Siefer, G., Bett, A.: Analysis of temperature coefficients for III-V multi-junction concentrator cells. Prog. Photovoltaics Res. Appl. **22**(5), 515–524 (2014)
24. Storn, R., Price, K.: Differential evolution: a simple and efficient adaptive scheme forglobal optimization over continuous spaces.Technical report TR-95-012 (1995)
25. Wang, L.X., Mendel, J.M.: Generating fuzzy rules by learning from examples. IEEE Trans. Syst. Man Cybern. **22**(6), 1414–1427 (1992)