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A differential evolution proposal for estimating the maximum power delivered by CPV modules under real outdoor conditions

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A B S T R A C T

Concentrating photovoltaics is an innovative alternative to flat-plate module to produce cost-competitiveness electricity. It is based on the use of optical system of reduced cost which is able to concentrate the solar light on a very small surface (high efficiency solar cell). At present, this technology has a marginal position in photovoltaic market and to take off needs to increase the confidence of the public and private sector. A better understanding of the concentrating photovoltaics technology electrical performance under real meteorological conditions would improve this situation. Because the bankability of a concentrating photovoltaics plant is addressed through the modelling of its energy production, an accurate estimation of the maximum power of the these modules is crucial to achieve it. Accordingly, the commercial evolution of concentrating photovoltaic technology demands prediction models for estimating the maximum power delivered by a concentrating photovoltaic module under real atmospheric conditions. Until now the only established standard method for outdoor power rating of this type of modules (ASTME-2527-09, defined by the American Society for Testing and Materials) does not consider the impact of the direct normal irradiance spectral distribution. The solar spectrum has an important influence on the electric performance of multijunction solar cells which composes concentrating photovoltaic modules.

In this work, an analysis of the inclusion in the prediction model of the solar spectrum by means of two indexes (spectral matching ratio and the average photon energy) and different spectral intervals is performed. Then, a differential evolution proposal for the estimation of regression coefficients for the two multivariable regression models is described. The accurate calculation of the model parameters reveals relations among the atmospheric conditions very useful for the experts. The multivariable regression models have been applied to two different concentrating photovoltaic modules, obtaining mean absolute percentage error values within the range 1.91–3.94%. The use of these accurate models for the estimation of the maximum power would allow to estimate the electric production of a concentrating photovoltaic power plant and the analysis of its costs and profitability, with the consequent benefits for the commercial development of this 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 materials (Law et al., 2010). These solar cells are expected to reach values of efficiency above 50% in the near future (Luque, 2011; Pérez-Higueras, Muñoz, Almonacid, & Vidal, 2011).

CPV technology has numerous benefits like higher energy density, higher efficiency, needs of lower surface and lower semiconductor material requirements (Chan, Brindley, & Ekins-Daukes, 2014; Swanson, 2000; Kurtz, 2009). Nevertheless, some technical

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and economic barriers must be removed to reduce the electricity production costs using this technology and to make it really competitive. In this sense, to CPV technology takes off is necessary to continue the economical and technical support of pilot projects which would permit to increase the confidence of the private and public sector. A better understanding of the electrical performance of such technology would improve this situation.

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 (Gupta, 2013; Leloux, Lorenzo, Garca-Domingo, & Gueymard, 2014). 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 generalised 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. In this sense, the Working Group 7 (WG7) of the International Electrotechnical Commission (IEC) is currently working in a procedure for this aim, but it is still in progress (Muller, Kurtz, & Rodríguez, 2013). According to this, the existence of an accurate and easily reproducible methodology which allows to estimate the electric behaviour of a CPV module, could increase the investors' confidence on this technology, making it to expand its participation at market level.

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. Despite the existence of some proposals in the literature to calculate the maximum power of a CPV module considering different input variables and alternative ways of modelling the spectral distribution, none of them have become definitive or generalised. 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*). At the same time, the multiple linear equations proposed are divided into two intervals, considering the SMR and APE values which coincide with the standard spectral distribution as turning points. This permits the implementation of the proposed model using the experimental measures given by two alternative devices: spectro-radiometer or triband spectro-heliometer.

As has been previously demonstrated (Domínguez, Antón, Sala, & Askins, 2013), the *DNI* spectral distribution negatively influences the P_M delivered by CPV modules, as it separates from the AM1.5D (ASTM G173-03, 2012) standard one, from which the modules were manufactured. Due to the previous reasoning, this work proposes the use of two different equations for each index, one for each spectral interval. 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. The optimisation of these equations is performed through the use of differential evolution (DE) which is a simple and effective versatile function optimisation based on evolution strategies. It stands out due to the diversity introduced in the evolutionary process since the searching is oriented through differences between individuals of the population. Moreover, it is important to note that DE is efficient since it has a linear complexity.

So, in conclusion, this paper proposes a model formed by multiple linear equations to evaluate the P_M delivered by different CPV modules, as a function of the following atmospheric conditions:*DNI*, T_A, W_S, and *DNI* spectral distribution through two alternative indexes: *SMR* and *APE*. This estimation model is, at the same time and with the objective of increasing its accuracy, divided into two different spectrum intervals. To obtain the regression coefficients which best fit the equations which compose the proposed model, a data mining algorithm based on DE was implemented.

The contribution is organised as follows: Section 2 describes the background of the presented work. Section 3 introduces the use of two indexes to define the influence of *DNI* spectral distribution on the CPV modules' electrical performance. Section 5 outlines the experimental framework. Section 6 shows the results obtained, and finally, some concluding remarks and future research directions are outlined.

2. Background

In this section, basic aspects concerning CPV technology are exposed in Section 2.1. The main concepts in order to facilitate the understanding of the electric behaviour of CPV modules under changing atmospheric conditions and some models introduced by other authors for P_M prediction, are described. Secondly, in Section 2.2 principal features of the DE algorithm are summarised and presented.

2.1. 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 (Herrero et al., 2012). 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 (Luque, Sala, & Luque-Heredia, 2006).

As it has been mentioned in the introduction, the ASTM E-2527-09 is the unique defined standard to evaluate the P_M delivered by CPV modules. Nevertheless, this standard does not consider the influence of the solar spectral distribution on the electric performance of CPV modules.

In Section 2.1.1, the main atmospheric parameters whose influence must be taken into account in the evaluation of CPV modules electric performance, are described. There are different models proposed by other authors which estimate, through different techniques, the P_M of a CPV module. However, none of these models consider all the atmospheric conditions previously described.

2.1.1. Study of influential atmospheric conditions on the electric performance of CPV modules

First of all, it is necessary to define and describe the atmospheric conditions whose impact must be considered as influential when estimating 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. If the incident solar spectrum differs from the AM1.5D standard (for which CPV modules are optimised), the MJ solar cells do not work as expected, offering a lower value of short circuit current and consequently a lower delivered P_M (Meusel, Adelhelm, Dimroth, Bett, & Warta, 2002; Kinsey & Edmondson, 2009; Philipps et al., 2010). As explained above, CPV modules are, in most of the cases, composed of MJ solar cells, so they are also influenced by these described atmospheric parameters. Some recently works study this influence through the analysis of the performance of CPV modules (Araki, Kemmoku, & Yamaguchi, 2008; Peharz, Siefer, & Bett, 2009; Fernández, Pérez-Higueras, García Loureiro, & Vidal, 2013), CPV systems (Strobach et al., 2012; Ghosal, Burroughs, Heuser, Setz, & Garralaga-Rojas, 2013), or big CPV plants (Bowman, Jensen, & Melia, 2012).

As can be observed, some of these works include the air temperature and the wind speed as initial significant parameters in the study and analysis of the electric performance of CPV systems.

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 (Nishioka et al., 2006; Kinsey et al., 2008; Siefer & Bett, in press; Helmers, Schachtner, & Bett, 2013). The same behaviour is observed when analyzing the impact of the temperature on the electric performance of CPV modules equipped with MJ solar cells (Peharz, Ferrer Rodríguez, Siefer, & Bett, 2011a). However, the own disposition of the MJ solar cells inside the CPV module makes it very difficult to measure their temperature. There are some methods to estimate the temperature of the MJ solar cells (Ju, Vossier, Wang, Dollet, & Flamant, 2013), or the temperature of the whole CPV module (Peharz, Ferrer Rodríguez, Siefer, & Bett, 2011b). Nevertheless, these methods require a previous knowledge about specific electric characteristics of the MJ solar cells, or coefficients which depend on each module itself. These parameters could be calculated through a solar simulator. Instead of this, in this work, and as has been done in several previous studies (Araki et al., 2008; Muller, Marion, Rodríguez, & Kurtz, 2011; Fernández et al., 2012, 2013), T_A is considered as influential factor, given a direct relation between cell temperature and T_A (Almonacid, Pérez-Higueras, Fernández, & Rodrigo, 2012; Antón et al., 2012).

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, has led the study and analysis of the effect of this parameter by other authors (Muller et al., 2011; Araki et al., 2008). The 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 (Castro et al., 2013). However, high W_S values can also exert a negative effect of misalignment on the tracker (Lin & Fang, 2013), displacing the MJ solar cells from their optimum arrangement in the solar beam direct trajectory.

2.1.2. Models for the estimation of CPV modules maximum power

A review of the main models for estimating the P_M of CPV modules has been recently published (Rodrigo, Fernández, Almonacid, & Pérez-Higueras, 2013). 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.

Hereunder some models proposed by other authors, which calculate the P_M of CPV modules, are exposed. It must be taken into account that the error obtained is expressed in a different way in each of those models, being difficult to compare each other.

ISFOC (Rubio, Martínez, Perea, Sánchez, & Banda, 2009) applied the multiple linear equation given by ASTM E2527-09, trying to obtain the regression coefficients: a_1, a_2, a_3, and a_4, which form the following equation:

$$P_M = DNI\,(a_1 + a_2 DNI + a_3 T_A + a_4 W_S) \quad (1)$$

where:

- P_M (W) : maximum power.
- DNI (W/m^2) : direct normal irradiance.
- T_A (°C) : ambient temperature.
- W_S (m/s) : wind speed.

The regression coefficients were obtained through a Matlab function, with five days of real outdoor data, obtaining an error of 2.93%. This error is expressed as the difference, in percentage terms, between the P_M of the CPV module under determined standard conditions, and the nominal value of P_M according to the manufacturer specifications. The used data were previously filtered so that the DNI must be higher than 700 W/m^2.

In the same way, a multiple linear regression method to obtain the P_M delivered by 4 different CPV module models was introduced in Peharz et al. (2011b). This P_M is expressed as a function of DNI, Spectrum factor (Z) and module temperature (T_{module}), as shown in the equation:

$$P_M = c_{DNI} DNI + c_Z Z + c_T T_{module} + K \quad (2)$$

where:

- P_M (W): maximum power.
- DNI (W/m^2): direct normal irradiance.
- Z (–): spectrum factor.
- T_{module} (°C): module temperature previously calculated through a model developed by the authors of the work.
- K: constant.

This multi-linear equation was modified by adding a quadratic term for one of the CPV modules, after observing a turning point in its efficiency value for $Z = 0.015$. The updated equation was expressed as follows:

$$P_M = c_{DNI} DNI + c_{Z2} Z^2 + c_Z Z + c_T T_{module} + K \quad (3)$$

This regression methodology did not take into account the W_S influence, and as described below, proposed an equation with a quadratic term to predict the P_M for one of the implied CPV modules. The equation defined for the rest of the CPV modules was linear. This methodology obtained absolute Root Mean Square Error (RMSE) values of 1.3 W, 1.2 W, 1.6 W and 0.6 W for module 1, module 2, module 3 and module 4, respectively. The nominal values of P_M for these CPV modules were: 54.0 W, 50.1 W, 44.0 W and 15.7 W, respectively.

In Fernández, Almonacid, Rodrigo, and Pérez-Higueras (2013) the authors proposed a model to estimate the P_M of CPV modules from outdoor real atmospheric conditions. In this model, this P_M is expressed as a function of the following climatological conditions:

$$P_M = f\,[DNI, T_A, AirMass\,(AM)] \quad (4)$$

The *AM* was considered as an approximation of the real solar spectrum, and used to define its influence. Otherwise, the W_S influence was not taken into account. The model proposed two different equations to predict the electric performance of the CPV modules, in function of the *AM* value:

- When $AM \leqslant 2$, it was confirmed that there was no influence of the *AM* on the P_M delivered by the module, so the equation was expressed as follows:

$$P_M = \frac{P^*}{DNI^*} DNI(1 - \delta(T_A - T_A^*)) \tag{5}$$

  where P^* is the value of the maximum power calibrated by the authors for $DNI = 850\ \mathrm{W/m^2}$, $T_A : 20\ ^\circ\mathrm{C}$, $AM : 1.5$ and wind speed values lower than 1 m/s. T_A^* is considered as 20 °C and δ is the coefficient which defines the impact of T_A on the P_M.
- Otherwise when $AM > 2$, an AM linear correction was included to the equation:

$$P_M = \frac{P^*}{DNI^*} * DNI(1 - \delta(T_A - T_A^*)) * (1 - \varepsilon(AM - AM_2)) \tag{6}$$

  where ε is the coefficient which defines the impact of *AM* on the P_M, being AM_2 the air mass value from which this parameter begins to influence the P_M of the modules.

By regression analysis, the values of δ and ε, for the two studied CPV modules, were obtained. After the comparison of the predicted and the measured value of P_M, relative RMSE values of 3.38% and 3.48% are respectively obtained for module A and module B.

In addition, artificial neural networks (ANN) can also be applied to obtain the P_M of a CPV module working under realistic atmospheric conditions. In this sense, in Almonacid, Fernández, Rodrigo, Pérez-Higueras, and Rus-Casas (2013) a multilayer perceptron (MLP) composed of 5 input neurons: *DNI*, *AM*, precipitable water (*PW*), T_A and W_S was proposed to estimate the P_M of CPV modules, obtaining a relative RMSE value of 3.29% for the test dataset. In the same way, in Rivera, García-Domingo, Del Jesús, and Aguilera (2013), CO^2RBFN, an evolutionary cooperative-competitive algorithm for the design of radial basis neural networks was applied to the calculation of the P_M delivered by a CPV module. The proposed methodology used the *DNI*, *APE*, T_A and W_S as inputs to the model, obtaining an absolute RMSE value of 3.93 W for the test dataset.

2.2. Differential evolution

The objective of this paper is to deepen in the characterisation of CPV modules using the multivariable regression equations. Thus, new variables are considered in the ASTM standard and their coefficients must be determined. Throughout the literature, in real optimisation problems have been used different meta-heuristics such as immune systems (Yildiz, 2009a, 2009c, 2009b), bee colony (Yildiz, 2013a, 2013d), cuckoo search (Ismail & Yildiz, 2012; Yildiz, 2013b) or particle swarm optimisation (Yildiz, 2012b; Yildiz & Solanki, 2012), for example. In this paper, a DE approach is employed in order to characterise the CPV modules.

The evolutionary algorithms are stochastic algorithms for optimising and searching based on the natural evolution process. These algorithms were introduced by Holland (Holland, 1975). Different computational paradigms can be found within EAs: genetic algorithms (Goldberg, 1989; Holland, 1975), evolution strategies (Schwefel, 1995), evolutionary programming (Fogel, 1995) and genetic programming (Koza, 1992). Within the evolution strategies can be found the DE which was defined by Storn and Price (1995) 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. It is important to note the final replacing where only the generated individual is included in the new population if it outperforms to the original one. A complete review about DE can be observed in Das (2011).

According to the original definition of the algorithm, its main stages are:

1. Initial population (*Pop*) is generated in a random way.
2. Following population in the evolutionary process is completed with the following process:
   (a) For each original individual Ind_m, three individuals are randomly extracted (Ind_0, Ind_1 and Ind_2) from the population.
   (b) A mutated individual (Ind_{off}) is generated with the previous three individuals according to Eq. (7).
   (c) Next, a recombination between the initial and mutated individuals (Ind_m and Ind_{off}) is performed in Ind_{off} as can be observed in Eq. (8).
   (d) Finally, the individual with the best adaptation between the initial (Ind_m) and recombined (Ind_{off}) individuals will be introduce in the population.
3. Process finishes when the number of generations is reached.
4. Best individual of the final population is extracted.

The mutated individual is generated through the following equation:

$$Ind_{off} = Ind_0 + F(Ind_1 - Ind_2) \tag{7}$$

where F is scaled factor for the mutation operator. On the other hand, the recombined individual is obtained in a probabilistic way where for each gene ($j = 1, \ldots, n$ where $n = numberofgenes$) of the individual is performed the following equation:

$$Ind_{off}[j] = \begin{cases} Ind_{off}[j] & \text{if } rand[0,1] \leqslant 0.5 \\ Ind_m[j] & \text{otherwise} \end{cases} \tag{8}$$

Throughout the literature the basic mechanisms of techniques based on DE provide good results in optimisation problems, specially for continuous optimisation (Neri & Tirronen, 2010; Yildiz, 2012a; Yildiz, 2013c). They are simple and efficient models which therefore have often been employed for solving various engineering problems such as the pioneering works (Storn, 1996; Masters & Land, 1997; Thomas & Vernon, 1997; Chang & Chang, 1998). On the other hand, the use of DE in the PV domain has been widely used for different authors recently.

- In Ishaque, Salam, Taheri, and Shamsudin (2011) and Ishaque, Salam, Mekhilef, and Shamsudin (2012) authors performed a complete experimental study in order to determine the best computational method between a genetic algorithm, a particle swarm optimisation and two DE algorithms to build an efficient and accurate photovoltaic system simulator.
- A method based on DE for determining the parameters of photovoltaic modules with the main objective of obtaining a valuable design tool for photovoltaic system designers was presented in Ishaque and Salam (2011).
- In Ramaprabha and Mathur (2011) DE is applied in order to address the maximum power point for tracking photovoltaic modules under partial shaded conditions.
- Seme and Stumberger published in Seme and Stumberger (2011) and Seme, Stumberger, and Vorsic (2011) a predictive algorithm based on DE in order to know the solar angle in photovoltaic modules for optimising their power.

- In Gómez-Lorente, Triguero, Gil, and Espín-Estrella (2012) the design of photovoltaic plants based on solar tracking with the minimum electric losses possible with different soft computing techniques such as DE is optimised.
- The simulation of solar systems is performed through different parameters. The optimisation of these parameters was performed in Gong and Cai (2013) through an improved DE algorithm.
- In Ye and Wang (2014) the solar cell model parameters from current–voltage (I–V) characteristics are determined. It was demonstrated that the I–V curve derived from the parameters extracted by the DE approach is in good agreement with the experimental or simulated I–V data.
- An improvement control method for solar auto-tracking based on DE is presented in Hu, Wang, He, and Wang (2014). In this way, results present a full application of the solar energy, and reducing the energy-loss of drive motor in the dynamic tracking process.
- A heuristic approach based on a DE algorithm was employed to perform an efficient optimisation of the conventional radial staggered heliostat field layout in the contribution (Atif & Al-Sulaiman, 2014). The model calculates all the required optical performance parameters at every step of the optimisation process for each heliostat and consequently more reliable results are obtained.
- In Soon-Tye, Mekhilef, Yang, and Chuang (2014) a DE based optimisation algorithm to provide the globalised search space to track the global maximum power point is proposed. The experimental results show that the proposed algorithm is able to converge to this point in less than 1.2 s with high efficiency.
- An improved adaptive DE with crossover rate repairing technique and ranking-based mutation is proposed in Lian-Jianga, Maskella, and Patrab (2013) in order to fast and accurately extract the solar cell parameters which play an important role in the simulation and design calculation the photovoltaic systems. The experimental results indicate the superiority of this proposal in terms of the quality of final solutions, success rate, and convergence speed.

As can be observed in this brief summary authors have applied DE for solving different problems within PV field. The main goals were the modelling and optimising of PV modules and/or plants. The proposal presented in this paper considers the use of DE in order to estimate the P_M delivered by a CPV module under determined influential atmospheric conditions.

3. The use of *SMR* and *APE* indexes to characterise the *DNI* spectral distribution

As introduced in Section 1, this paper proposes to modify the equation given by ASTM E-2527-09 methodology to calculate the P_M delivered by CPV modules. This modification consist of including the influence of the solar spectrum by means of an additional addend to the multiple linear equation.

When evaluating the influence of the solar spectrum distribution on the electric performance of CPV modules, two different indexes can be considered: *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 (Domínguez, Askins, & Sala, 2009). 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:

$$SMR\,(AM1.5D)^{TOP-junction}_{MIDDLE-junction} = \frac{DNI_{TOP-junction}}{DNI_{MIDDLE-junction}} \tag{9}$$

where $DNI_{TOP-junction}$ 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.

Fig. 1 shows the relation between the *SMR* and *DNI* for the experimental campaign carried out in Jaén, described in Section 5.1. As appreciated, with low values of *DNI*, red-richer spectrums are registered during the first and last hours of the day. Otherwise, under cloudy conditions, spectral distributions with a higher content in blue are obtained. Furthermore, under high values of *DNI*, which correspond to clear sky conditions, the *SMR* value is closer to the unit, so the spectral distribution is therefore nearer to the AM1.5D standard one.

In Fig. 2, two histograms are shown, which represent the percentage of collected data for different *DNI* and *SMR* intervals, during the experimental campaign.

As can be appreciated, most of the registered data are collected under high *DNI* values, and under spectral distributions with a high blue-content. The *SMR* influence on the normalised Short Circuit Current (ISC_N)-and therefore on the P_M-generated by a CPV module is demonstrated in Fig. 3. The *ISC* values were normalised 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.

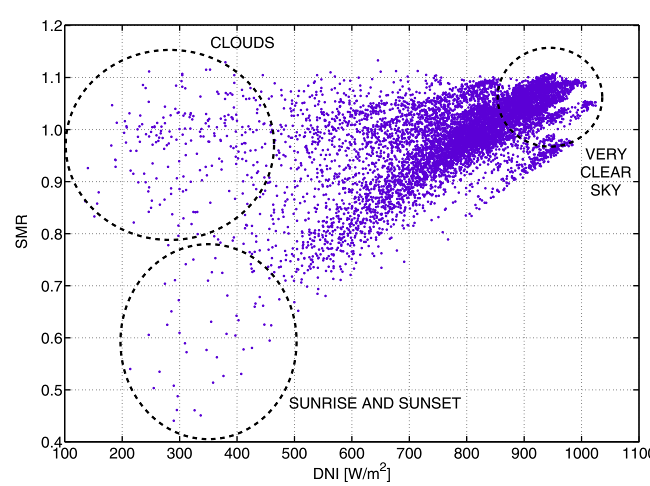

Fig. 1. Relation between *DNI* and *SMR*.

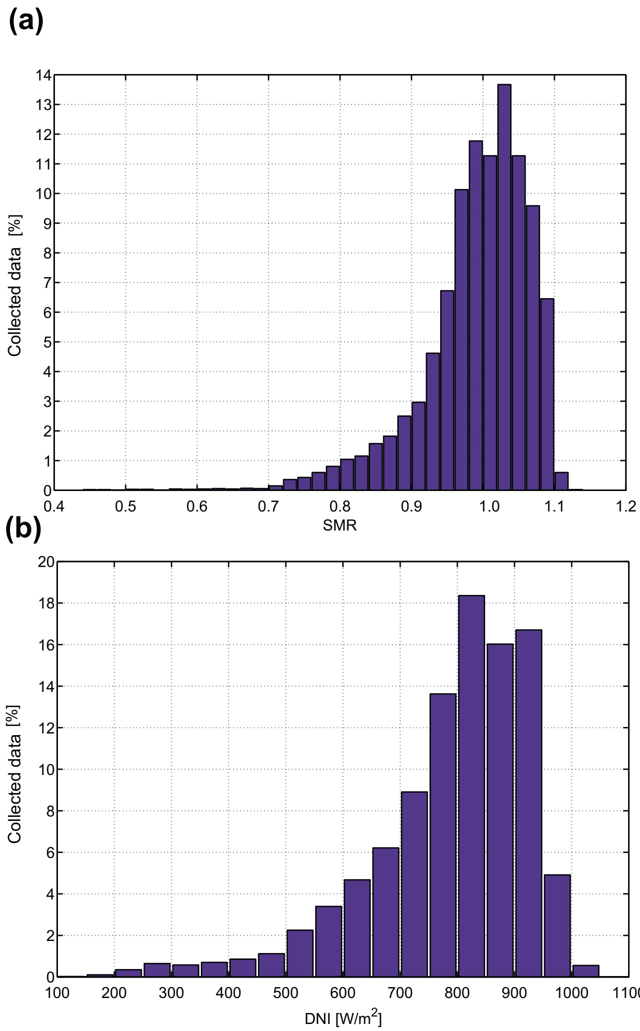

Fig. 2. Histogram of percentage of collected data divided in function of *DNI* (a) and *SMR* (b).

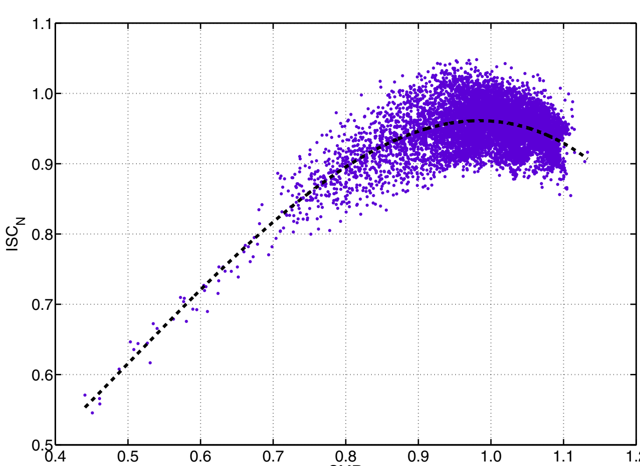

Fig. 3. Relation between *SMR* and ISC_N.

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 (Minemoto, Nakada, Takahashi, & Takakura, 2009). 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:

$$\frac{\int_a^b E_\lambda(\lambda)d\lambda}{\int_a^b \phi_\lambda(\lambda)d\lambda} \tag{10}$$

where:

- E_λ (W/(m^2 nm)): spectral irradiance.
- ϕ (1/(m^2 nm 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 spectro-radiometer 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 (Moreno Sáez, Sidrach-De-Cardona, & Mora-López, 2013; Ishii, Otani, Takashima, & Xue, 2013; Piliougine, Elizondo, Mora-López, & Sidrach-de Cardona, 2013; Cornaro & Andreotti, 2013; Nofuentes, García-Domingo, Muoz, & Chenlo, 2014). There also exists a work, which used the *APE* index to define the solar spectrum influence on the electric performance of a CPV system (Husna, Shibata, Ueno, Ota, & Minemoto, 2013).

Three different *DNI* spectral distributions, with their respective associated values of *APE* and *SMR*, were represented in Fig. 4.

Fig. 5 shows the intrinsic relation between both indexes used to measure the influence of the spectrum: *SMR* and *APE*. As can be appreciated, this relation 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:

$$f(x) = p_1 x + p_2 \tag{11}$$

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

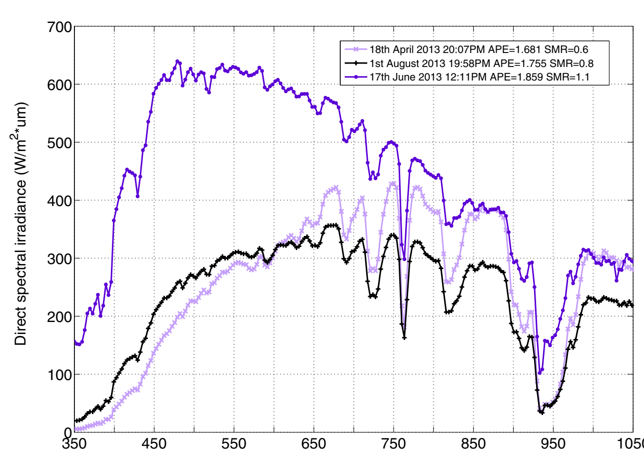

Fig. 4. Representation of different *DNI* spectrum distributions.

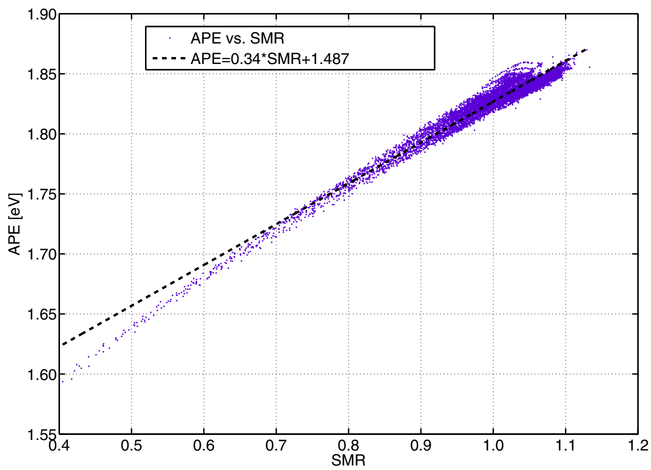

Fig. 5. Relation between *SMR* and *APE*.

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.

4. Differential evolution for the optimisation of CPV regression model

Based on ASTM E-2527-09 methodology, and modifying it to include the impact of the solar spectrum, the work presented in this paper proposes obtaining the regression coefficients through DE proposal with the best fit the multiple linear equations.

The core of this DE-proposal is based on the equations for the calculation of the P_M which can be observed in Tables 1 and 2. Both equations contain different regression parameters $(a_1^a, a_2^a, \ldots, a_5^b)$ which are associated to each atmospheric condition. The influence of these conditions is widely described in Section 2 where *DNI*, Spectrum (through *SMR* or *APE*), T_A and W_S are inputs to the modelling and the P_M delivered by the studied CPV modules under specific atmospheric conditions, is the output of the model.

Considering the definition of the regression equations for this evolutionary algorithm, representation of the individuals is based on the different parameters to optimise the atmospheric conditions, which can be observed in Table 3 where a gene for each coefficient is used: $a_1^a, a_2^a, \ldots, a_5^a, a_1^b, \ldots, a_5^b$. The initial value of these coefficients are generated in a random way within the domain $[-1, 1]$.

The goal of the DE-proposal is to evolve, throughout the different generations, the values of these regression parameters in the individuals of the population in order to obtain the lowest possible error between the P_M predicted with the regression equations (using these regression coefficients) and real P_M values. Specifically, this error is the fitness function of the individual and it is calculated through the mean absolute percentage error (MAPE) between the real and predicted P_M values as shown in the following equation:

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{predictedP_M - realP_M}{realP_M}\right| \quad (12)$$

where N is the number of samples of the dataset.

Evolutionary process is based on the scheme of Algorithm 1. This algorithm is controlled through the number of generations. For each generation of the process, a new individual for each initial one is generated through mutation with others three individuals (which were selected in a random manner). In this way, one offspring is obtained by the algorithm for each initial one. Through a random process, a recombination between both individuals (initial and offspring) is generated, and at the end of the process, the individual included in the population of the next generation is the best one between the recombined individual and the initial one.

Algorithm 1. Operation scheme of DE-proposal

```
BEGIN
Initialises & Evaluates Pop(t)
Increments the number of generations
repeat
  for i = 1 to Size(Pop(t)) do
    Ind_0, Ind_1, Ind_2 = SelectIndividuals(Pop(t))
    for j = 1 to SizeIndividual() do
      if Random(0,1) ⩽ 0.5 then
        Ind_off[j] = Ind_0[j] + F(Ind_1[j] − Ind_2[j])
      else
        Ind_off[j] = Ind_i[j]
      end if
    end for
    Evaluate Ind_off
    if Ind_off.fitness ⩽ Ind_i.fitness then
      Ind_off in Pop(t)
    else
      Ind_i in Pop(t)
    end if
  end for
  Increments the number of generations
until Number of generations is not reached
Return the individual with the best fitness
END
```

5. Experimental framework

In this section the main details of the measurement system are presented in Section 5.1. Additionally, the main features and parameters of the experimental framework are described in Section 5.2.

5.1. Measurement set-up

The proposed experimentation was implemented to two different models of CPV modules, whose main characteristics are resumed in Table 4. To measure and register the data used in the presented experimentation, an Automatic Test & Measurement System designed by IDEA research group was used (Rivera et al., 2013).

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 *M*1 and 4710 samples for the module *M*2. A less amount of data for module *M*2 was obtained because they had to be filtered due to shadowing problems. The atmospheric measures were registered every 5 min using the outdoor devices specified in Table 5 and described below:

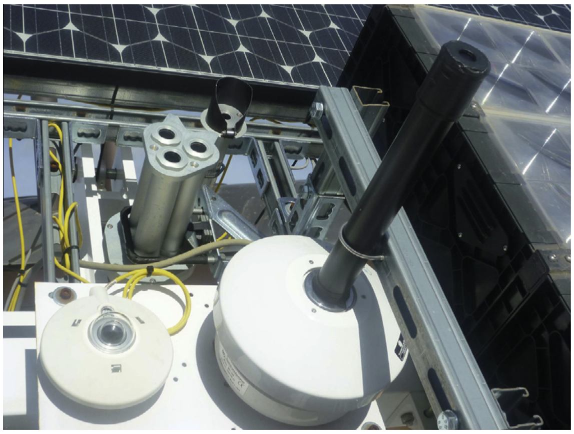

Fig. 6. Outdoor measurement devices: pyrheliometer, spectro-radiometer and spectro-heliometer.

Fig. 7. Outdoor measurement devices: anemometer and temperature probe.

Table 1
Equation for the calculation of P_M using *SMR* index as additional addend.

SMR as additional addend considering $SMR_{AM1.5} = 1$
if $SMR < SMR_{AM1.5}$ $P_m = DNI\,(a_1^a + a_2^a DNI + a_3^a T_A + a_4^a W_S + a_5^a SMR)$ elseif $SMR \geqslant SMR_{AM1.5}$ $P_m = DNI\,(a_1^b + a_2^b DNI + a_3^b T_A + a_4^b W_S + a_5^b SMR)$

Table 2
Equation for the calculation of P_M using *APE* index as additional addend.

APE as additional addend considering $APE_{AM1.5} = 1.83$
if $APE < APE_{AM1.5}$ $P_m = DNI\,(a_1^a + a_2^a DNI + a_3^a T_A + a_4^a W_S + a_5^a APE)$ elseif $APE \geqslant APE_{AM1.5}$ $P_m = DNI\,(a_1^b + a_2^b DNI + a_3^b T_A + a_4^b W_S + a_5^b APE)$

- A Kipp & Zonnen™ CHP 1 pyrheliometer to the measurement of the direct normal irradiance (*DNI*).
- An EKO™ 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.

Table 3
Representation of an individual for the algorithm.

a_1^a	a_2^a	...	a_5^a	a_1^b	a_2^b	...	a_5^b
−0.76	0.24	...	0.00	−0.01	−0.05	...	0.23

- 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™ 41382VC relative humidity & temperature probe to register the T_A and a Young™ 05305VM anemometer to measure the W_S.

The Automatic Test & Measurement System permits to simultaneously measure and register the P_M of the analysed CPV modules, together with the atmospheric conditions which influence their electric performance.

5.2. Experimental set-up

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. Otherway, 20% (test) of the whole dataset was used to validate the predictive capacity of the proposed model.

Moreover, different aspects must be considered in order to use the DE-proposal. On the one hand, it must be defined the parameters of the algorithm as number of generations and number of individuals for the populations which are 10,000 and 100, respectively. On the other hand, due to the nature of this stochastic algorithm, ten executions were performed and the execution with the best results were selected.

The results obtained for the DE proposal with the test data are compared with the ones provided by a multiple linear regression (*MLR*) method (Flury & Riedwyl, 1988) with the typical equation:

$$f(\vec{x}) = \beta_0 + \sum_{j=1}^{n} x_j \beta_j + e \tag{13}$$

where $\vec{x} = (x_1, x_2, \ldots, x_p)$ is a vector of inputs; β's are unknown coefficients, the variables input variables x_j and e being a random error.

The most popular estimation method for the coefficients, least squares, pick them to minimise the residual sum of squares.

$$RSS(\beta) = \sum_{i=1}^{n} (y_i - f(x_i))^2 = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 \tag{14}$$

Specifically, the fitted values β's are estimated using the R software.[1] It is important to highlight that this method is executed only once because it is a non-stochastic.

6. Experimental analysis

The MAPE between real P_M values and P_M values predicted by DE and MLR for the CPV modules under study ($M1$ and $M2$), are shown in Table 6.

As it can be confirmed, the algorithms implemented to calculate the regression coefficients which best fit the equations shown in Tables 1 and 2, provide error results very similar between them.

[1] http://www.r-project.org/.

Table 4
Main characteristics of the CPV modules under study.

Module ref.	Solar cells type	Number of solar cells	Concentration factor
*M*1	Multijunction – GaInP/Ga(In)As/Ge	25	550
*M*2	Multijunction – GaInP/GaInAs/Ge	6	625

Table 5
Measurement of atmospheric conditions by outdoor devices.

Atmospheric condition	Units	Outdoor device	Measures range	Figures
DNI	(W/m^2)	*Pyheliometer*	[140–1024]	Fig. 6
Spectrum APE	(eV)	*Spectro – radiometer*	[1.59–1.87]	Fig. 6
Spectrum SMR	(–)	*Spectro – heliometer*	[0.40–1.13]	Fig. 6
T_A	(°C)	*Spectro – heliometer*	[11.39–41.82]	Fig. 7
W_S	(m/s)	*Anemometer*	[0.04–20.50]	Fig. 7

Table 6
MAPE test results obtained by both implemented algorithms to the CPV modules under study.

Mod	Index	DE (%)	MLR (%)
*M*1	$SMR < 1$	3.07	3.06
	$SMR \geqslant 1$	2.17	2.19
	$APE < 1.83$	2.94	2.99
	$APE \geqslant 1.83$	2.05	2.06
*M*2	$SMR < 1$	2.45	2.47
	$SMR \geqslant 1$	3.08	3.94
	$APE < 1.83$	2.48	2.40
	$APE \geqslant 1.83$	2.59	1.91

Nevertheless, the DE algorithm obtained better results in the majority of the cases. In general, the obtained results show the capacity of both implemented methodologies to solve the proposed multiple linear model, with MAPE values within the interval [1.91–3.94]%. From the analysis of the MAPE values calculated for the two CPV modules under study, the possibility of using both *SMR* and *APE* indexes to define the influence of the *DNI* spectral distribution on CPV modules electric performance, is enhanced.

In Table 7, the regression coefficients obtained by the DE algorithm for the two analyzed CPV modules are presented.

It is important to highlight that the solar tracker which support the CPV modules under study, is optimised for the module *M*1. Because of that, the electrical parameters delivered by this CPV module *M*1 were considered as basis of the study of the influence of atmospheric conditions on the electrical behaviour of CPV modules. In this way, and according to the regression coefficients calculated by the DE-proposal for the module *M*1, 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 $SMR \geqslant 1$ or $APE \geqslant 1.83$. 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.

Some differences are observed between the electric performance of the two analyzed CPV modules and their dependence on the atmospheric conditions. This fact could be due to the existence of constructive variations between them, and also because the solar tracker is calibrated so that the module *M*1 works in an optimum way. In future experimental campaigns it is proposed to recalibrate the solar tracker to make the module *M*2 to work in an optimum manner. This would allow to compare those results with the ones obtained in the work presented in this paper, and would permit to obtain more generalised conclusions.

Despite the latter, and after analyzing the MAPE values calculated for the multiple linear regression model, it is concluded that this model is suitable for simple and accurate predictions of the P_M delivered by different CPV modules.

7. Conclusions and future research directions

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. This expression allows the calculation of the P_M as a function of 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

Table 7
Regression coefficients obtained by DE methodology for the two CPV modules.

Module	Index	a_1	a_2	a_3	a_4	a_5
*M*1	$SMR < 1$	0.076423	−1.63E−05	−1.11E−04	3.00E−04	0.062229
	$SMR \geqslant 1$	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
	$APE \geqslant 1.83$	0.219101	−8.79E−06	−3.75E−04	3.06E−04	−0.044181
*M*2	$SMR < 1$	0.045007	−6.15E−06	−7.52E−05	−5.78E−05	0.025581
	$SMR \geqslant 1$	0.063086	−7.10E−06	7.86E−05	-1.17E−05	0.002795
	$APE < 1.83$	0.000072	−7.98E−07	−4.80E−04	−5.23E−05	0.035437
	$APE \geqslant 1.83$	−0.023640	−8.73E−06	5.18E−05	−6.57E−05	0.049991

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*).

Additionally, the proposed model consider a division between two spectral intervals. The influence of the *DNI* spectral distribution on the P_M delivered by CPV modules is marked by a turning point which coincides with the AM1.5D standard spectral distribution. Attending to this influence, the model proposed the use of two different multiple linear equations, corresponding to each of the two considered spectral intervals.

To calculate the regression coefficients which best fit the multiple linear equations which compose the proposed model, an evolutionary algorithm based on DE was implemented. Additionally, and to compare the worthiness of this DE algorithm, a simple MLR method was used. The regression coefficients were calculated from the experimental dataset measured for two CPV modules under study.

Finally, the P_M values obtained by the model (through the regression coefficients calculated by means of DE and MLR algorithms) under determined atmospheric conditions, were compared with the corresponding real P_M values for the two analyzed CPV modules. As a result, it is concluded that the proposed model obtained MAPE values within the range 1.91–3.94%. In PV field, errors between 0% and 2% are classified as a very good predictions, in the interval between 2% and 3.5% as good, and within the range 3.5–5% they are considered as satisfying.

This work presents a DE approach in order to calculate the regression coefficients in an extension of the ASTM E2527-09 standard. The extended model considers the spectral distribution as one of the input environmental conditions for the calculation of the maximum power delivered by a CPV module. To do so, two different variables have been analysed and included: *SMR* and *APE*. The importance of the proposed model is highlighted with its suitability when estimating the P_M delivered by two different CPV modules. The proposal is a simple and accurate methodology to obtain the P_M under influential atmospheric conditions: *DNI*, T_A, W_S and *SMR* or *APE* (depending on the available outdoor device, spectro-heliometer or spectro-radiometer respectively). The application of the model to the forecasting of the P_M delivered by big CPV power plants would suppose an increasing of the investors' confidence and a consequent commercial development of this CPV sector.

As future research directions to this paper we propose:

- To analyse the possibility of obtaining multiple linear regression equations to calculate the main parameters of a CPV module I–V curve, such us maximum voltage and maximum current, open circuit voltage and short circuit current.
- To apply the prediction model to estimate the energy generated by big CPV power plants under determined atmospheric conditions previously introduced as inputs to the model.
- To include additional atmospheric conditions and study the possible relations between them.

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