The Design of a Low-Cost Radiometric System for Photovoltaic Solar Cells

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***Abstract*—Photovoltaic (PV) cell manufacturers use a standard spectrum when designing and characterizing their systems. However, various authors have shown that variations in the spectrum of light during different seasons and/or in different locations have a significant impact on the efficiency of PV cells. Consequently, metrics such as the average photon energy, the useful fraction, and the weighted useful fraction have been proposed and successfully used to demonstrate the relationship between the spectrum of the incident radiation and PV cells efficiency. In this work, we propose the use of an inexpensive radiometric system to accurately determine the spectrum of incident light and, hence, some of these efficiency metrics in real time. This system could easily be integrated within a PV cell system so that these parameters are available for both system assessment and possibly for the maximum power point tracking systems that can deal with challenging partial shading conditions.**

***Index Terms*—Sensors, solar energy, spectral analysis.**

I. Introduction

VARIATIONS in the spectrum of incident irradiation significantly affect the efficiency of photovoltaic (PV) modules [1]. Unfortunately, the standard test conditions used to assess the performance of PV cells very rarely occur when a system is installed and operated [2]. Consequently, the actual efficiency of PV cells, particularly those based upon materials with narrow spectral ranges, can vary by as much as $\pm35\%$ from that estimated from the standard test conditions [1]. In fact, some manufacturers have pointed out that once they are installed, their systems produce more power than expected [3]. In contrast, the underperformance of PV modules in sub-Saharan Africa may be due to the difference between the spectra in the standard test conditions and the actual spectra in these locations [4].

One study that highlighted the difference between results obtained from field trials and from standard test conditions was performed by Berman *et al.* [5]. In particular, during a study of aging effects in PV modules, this group found that after adjusting their measurement data to standard irradiance power and temperature conditions, the maximum power available from each module varied with both the season and the time of day. To show that this phenomenon was caused by spectral effects, they introduced the term photovoltaically active fraction (PAF). The PAF represents the fraction of incident radiation that consists of photons whose energy is larger than the bandgap of the PV material. Similarly, while investigating the potential importance of spectral effects on devices made from materials with different bandgaps, Gottschalg *et al.* used a parameter that they called the useful fraction (UF). This UF is the "ratio of the observed spectral irradiation in the useful spectral range of a PV device in question to the observed global irradiation" [6]. Using this ratio and spectral data measured in the U.K., they proposed explanations for previously observed variations in the efficiency of PV cells. In addition, they showed that both daily and seasonal variations in the spectrum of irradiation will influence the performance of PV cells [6]. Subsequently, Al Buflasa *et al.* showed that for a double-junction PV cell, there is a strong correlation between the UF and the ratio of the short-circuit current to the irradiation intensity [7]. In addition, Jardine *et al.* [8] have shown a strong correlation between the average photon energy (APE) and both UF and the short-circuit current in single-junction devices. Based upon these correlations, they have suggested that the APE is a useful metric when analyzing PV cell efficiency.

The PAF and UF have the advantage that they are relatively simple to calculate and take into account the properties of the substrate material used to manufacture the PV cells. However, they fail to take into account other factors that affect the actual spectral response of a particular PV cell design such as the doping of the material and/or the use of protective glass of different kinds. To take these factors into account, Simon and Meyer proposed the weighted useful fraction (WUF) [9]. For a PV cell design with a spectral response SR(λ) (for more details on how to experimentally measure SR, see [10]), irradiated by an illuminant with a spectrum $E(\lambda)$, the WUF is defined as

$$\mathrm{WUF} = \frac{\int_{\mathrm{cell-min}}^{\mathrm{cell-max}} E(\lambda)\,\mathrm{SR}(\lambda)\,d}{\int_{\mathrm{observed\_radiation-min}}^{\mathrm{observed\_radiation-max}} E(\lambda)\,d\lambda}. \tag{1}$$

Since UF is calculated assuming $\mathrm{SR}(\lambda) = 1$ in the range of the cell absorption in (1), UF is always bigger than WUF for a given cell technology. For PV modules made from monocrystalline silicon, the WUF in South Africa varies between 0.5743 and 0.5293 in the winter, while during the summer, the equivalent variation is from 0.6407 to 0.5927 [4].

The motivation for the various investigations into spectral effects has been the desire to understand the observed performance of different PV modules under actual operating conditions. However, the proven relationship between the various parameters, and either the efficiency of a PV module or its short-circuit current, may create an important opportunity to gather

Manuscript received February 23, 2016; revised May 18, 2016 and September 2, 2016; accepted September 13, 2016. Date of publication October 3, 2016; date of current version October 19, 2016. The work of S. Collins was supported by the U.S. Department of Commerce under Grant BS123456.

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Digital Object Identifier 10.1109/JPHOTOV.2016.2611241

information that could be used to survey a potential site prior to installation or to monitor the long-term performance of an installed system, particularly when a new type of PV module is deployed. However, this will only be an attractive proposition if the sensors used to gather the required information are inexpensive and, in the latter case, more stable than the material used to make the PV modules.

Previously, we have shown [11], [12] how data from a small optimum set of photosensitive sensors and spectral estimation algorithms can be used to obtain accurate colorimetric and spectral estimates of skylight radiance. The photosensors in this type of system might be manufactured by integrating Fabry–Perot filters, with a full-width at half-maximum (FWHM) of between 10 and 15 nm, on top of the pixels of an otherwise standard CMOS imager [13]. Alternatively, other manufacturers [14] provide similar filters, with an FWHM between 10 and 40 nm, which can be attached to individual silicon photodiodes to create sensors with relatively sharp spectral responses. There are, therefore, at least two different approaches to creating an inexpensive spectroradiometric system that can gather data on the spectrum of light irradiating any system, including a PV module or PV modules. The aim of the work reported in this paper is to investigate the number of sensors that will be required to estimate relevant spectral parameters.

Previously, the optimum set of sensors with Gaussian spectral responses required to reconstruct the spectrum of illuminating light was found using simulated annealing. We found that this optimization reduced the number of sensors required to perform this task. In addition to potentially reducing the cost of a system, the optimum set of sensors is more robust to noise and temperature changes. This result was found in computational simulations [11], as well as in actual systems [12]. Critically, these results suggest that it is should be possible to estimate the spectrum of daylight and skylight and, hence, parameters related to PV module performance, using a small number of sensors and simple data processing implemented on inexpensive hardware.

In this work, our interest is moved from skylight radiance [15] to daylight irradiance [16]. Moreover, since current PV cells are capable of capturing radiation from 300 to 1180 nm (in the case of c-Si cells), we also need to extend the spectral range of interest beyond the visible. Hence, the aim of this study is to investigate the feasibility of implementing an inexpensive system that can estimate daylight spectral irradiance in the range of interest for c-Si and a-Si PV cells. The system we computationally simulate here is based on the responses of a small set of sensors with Gaussian spectral and a spectral estimation algorithm [11] that can obtain accurate daylight spectral curves from the sensor responses in real time. These spectral data could be used to provide accurate estimates of any parameter of interest at different times. However, parameters such as UF and WUF require a sensor to determine the global irradiation. To avoid the need for this extra sensor, the work reported in this paper concentrates upon systems that estimate parameters, such as APE, that only require data from wavelengths between 300 and 1100 nm.

This paper is structured as follows. In Section II, we describe the experimental set of daylight spectral data we used in our study. In Section III, we show the method and procedure we followed to obtain spectral estimates of the radiation impinging on a PV cell, and how we can use this spectral information to infer interesting information that will relate to the PV cell efficiency. In Section IV, we show the results obtained from an optimized small set of Gaussian sensors and discuss the potential accuracy of such a system. Finally, a summary and conclusions are provided in Section V.

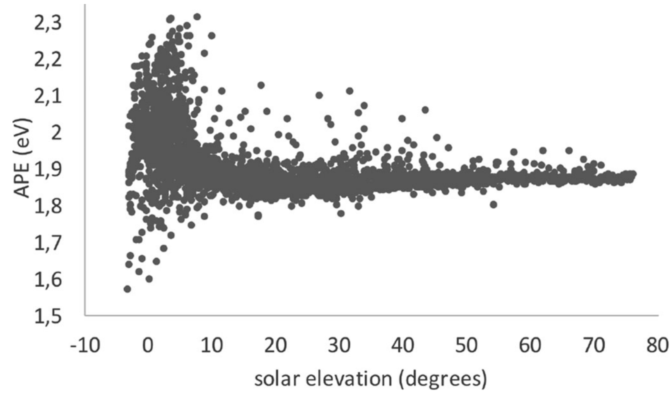

Fig. 1. APE of the whole dataset as a function of solar elevation.

II. Description of the Experimental Data

In order to obtain statistical significant results, we used a set of 2600 spectral daylight irradiance measurements taken in Granada (Spain, 37.18°N 3.60°W) over two years. This placement is close to a large solar power station [17]. Our data were acquired with a cosine receptor attached to the spectroradiometer; hence, the measured irradiance comes from the whole sky dome. More details about this set of spectral data can be found in [16], and the dataset is publicly available at http://colorimaginglab.ugr.es/pages/Data. These spectral data contain information in the range from 300 to 1100 nm in 5-nm steps and allow us to estimate the total number of photons that could be absorbed by any material according to its spectral absorptance, including both a-Si and c-Si. However, in this work, we will restrict our examples to the a-Si case, and all the calculations will be done in the total available spectral range of our dataset (300–1100 nm) in order to prove the general feasibility of our approach.

Previously, large changes in the spectrum of daylight have been observed between the middle of the day and both early morning and the evening. The results in Fig. 1 show that the APE calculated using the spectral response of a typical a-Si cell from [2] at different times of day is close to 1.9 eV (corresponding to a photon of 659 nm) for most of the day (that is for most of the solar elevations). However, huge APE variations (around 45%) can be seen at the smaller solar elevations that occur around sunset and sunrise, and even during the day, the APE can vary by 20%.

In the following sections, a subset of 100 spectra from the whole dataset is used as a training set. Spectral estimation algorithms, such as the one used in Section III, usually provide unrealistically good results when estimating the spectra in the training set. Hence, another representative set of spectra are used to test the accuracy of the spectral estimation method. These training spectra are selected according to a grouping algorithm proposed in a previous work [18], where we also proved that a small subset selected in this way can provide accurate and realistic spectral reconstructions of the whole test set.

III. Description of the System

In previous works [11], [12], we have been able to design and develop a simple multispectral imaging system that permitted us to obtain accurate spectra of skylight radiance from different points of the sky dome in Granada, on clear days, at different times of the day and during two years. The combination of a small set of optimized Gaussian sensors and the Imai–Berns spectral estimation method proved to be an excellent approach to solve this problem in the visual spectral range. In a similar work [18], we also proved that the Imai–Berns method (or a particular case of it, called linear pseudoinverse) can provide estimates of skylight spectral radiance from the responses of a three-sensor commercial scientific charge-coupled device camera, which were reliable enough to predict the optical depth, the Angström exponent, or cloud cover in real time [19].

Various spectral estimation algorithms exist [11], [20], which might be used for the purpose of this work. These algorithms rely on the statistical similarity between the spectra under analysis. Hence, covariance techniques—such as principal component analysis [20]—allow high-dimensional data (the spectra) to be obtained from low-dimensional inputs (the sensors responses). Most of these spectral estimation algorithms are based on the observation that a set of spectral curves belonging to a given kind of illuminant (both natural and artificial), or even the spectral reflectance curves belonging to a given kind of objects, can be accurately represented by a linear basis of reduced dimension [20]. Hence, linear methods can be used to calculate the spectral curves from the camera's sensor responses. Recently, some authors [21], [22] have also proposed the use of more sophisticated methods based on neural network prediction, spline interpolation, genetic algorithms, or logarithmic kernel, among others. However, the improvement in accuracy is marginal, while the computation time increases significantly. We, therefore, prefer to use the Imai–Berns method [23], since it is fast and robust and provides accurate results, as reported by various authors [11], [24].

Once the spectrum of the light irradiating a sensor has been estimated, this can be used to estimate one of several parameters of interest. One of the parameters that is potentially useful is the photon absorption rate (PAR) for a PV module, which is proportional to the short-circuit current that would be obtained. If the spectral response of the PV module is SR(λ), then PAR can be estimated as

$$\mathrm{PAR} = \int_{300\,\mathrm{nm}}^{1100\,\mathrm{nm}} E(\lambda)\,\mathrm{SR}(\lambda)\,\frac{\lambda}{hc}\,d\lambda. \tag{2}$$

For simplicity, this can be written in matrix form as

$$\mathrm{PAR} = \mathrm{SR}' \cdot \Lambda \cdot E \tag{3}$$

where Λ is an *N*-by-*N* diagonal matrix (assuming *N* sampling wavelengths) containing the product $\frac{\lambda}{hc}$ for each of the sampling wavelengths (*h* is Planck's constant, *c* is the speed of light in vacuum, and λ is the specific wavelength), *E* is an *N*-by-1 column vector containing the radiance received by the PV cell, and SR is an *N*-by-k matrix containing the spectral response of the *k* sensors in our system at the *N* sampled wavelengths (SR' means transposed). The main assumption of the Imai–Berns method [23] is to write the radiance *E* as an expansion of a low-dimensional linear basis. Details on this method can be found in many papers in the literature [11], [12], [20].

In our computational simulations using the Imai–Berns method to obtain spectral estimates, we modify different parameters affecting the design of the system, including the number of sensors and position and width of the spectral response of each sensor used, in order to find the combination providing the best result. We will also simulate different sensor heights in order to take into account different parameters that could affect the relative responsivity of individual sensors in a given set, for example, the variation of quantum efficiency with sensor central position at different wavelengths or variable exposure times.

When dealing with the question of how accurate our system needs to be, we face two challenges. First, which metric should we use to judge the accuracy of a spectral estimate system intended to work in a range wider than the visual (hence, colorimetric metrics are not valid). Second, what is the minimum accuracy that will permit the detection of variations in the efficiency of typical PV cells due to changes in the spectral composition of the impinging radiation.

Regarding the first question, since the power available to a PV cell is proportional to the PAR, then in addition to APE explained in Section I, the PAR should be a good metric. The error between the actual and estimated PAR in a spectral estimation system can be calculated as

$$\mathrm{PAR\ error} = \int_{300\,\mathrm{nm}}^{1100\,\mathrm{nm}} \left(E(\lambda) - E_{\mathrm{est}}(\lambda)\right)\mathrm{SR}(\lambda)\,\frac{\lambda}{hc}\,d\lambda \tag{4}$$

where, again, *E* is the spectrum of the light impinging the PV cell, E_{est} is the estimate of that spectrum, SR is the spectral responsivity of the PV cell, and *h* and *c* are Planck's and speed of light constants, respectively. Hence, for the purpose of this work, errors in the spectral estimates will be expressed in terms of PAR and APE for a PV cell with an SR.

A target accuracy of any estimation method can then be obtained by considering the temperature sensitivity of a PV cell. In particular, in addition to being dependent upon the illuminant spectrum, the performance of PV cells is also sensitive to temperature, showing increases of 0.3%/K in the case of c-Si, and approximately 0.1%/K in a-Si. We have also shown in Section II that the variation for APE can be as large as 20% during the main part of the day. Hence, an error between 0.1% and 1% would permit the detection of meaningful changes in the efficiency of the PV cell and, therefore, represent a good threshold for the accuracy required to a spectral estimation system for this application.

Noise is an external factor affecting the response of every electronic system. Hence, we will also simulate its effect in this

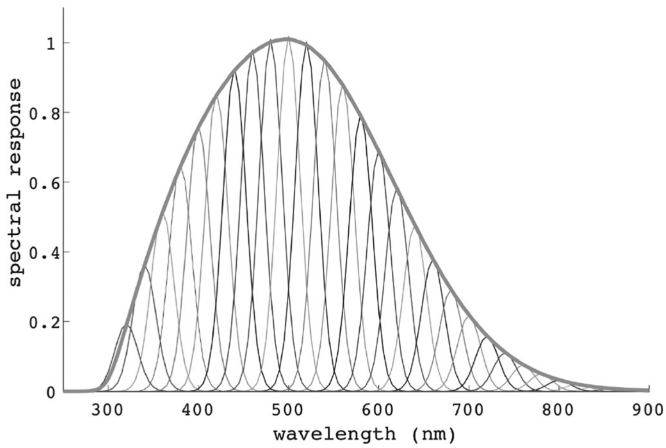

Fig. 2. Example of how a system of 28 sensors, whose spectral responses have an FWHM of 30 nm and whose peak central wavelengths are separated 40 nm, can be used to emulate the response of an a-Si PV cell.

work. For typical light capturing devices [25], [26], noise can vary between 2% and 3.5% of the total signal, depending on the exposure time required for image capturing. The corresponding signal-to-noise ratio (SNR) would be between 40 and 34 dB. For more sophisticated devices, which have some kind of sensor refrigeration, noise can be reduced to 1% (i.e., 40 dB of SNR). Moreover, some noise correction algorithms exist [26], [27] (multiple frames temporal averaging, for instance) that can reduce its effect for both refrigerated and nonrefrigerated devices, down to levels around 0.5% (46 dB of SNR) and 1%, respectively.

In our simulations, we will assume noise levels of 1% and 3%, which are equivalent to SNRs of 40 and 30 dB, respectively, since this level seems to be fairly realistic. However, we will also show some results obtained in noise-free situations in an attempt to analyze how accurate our approach can be, regardless of the effect of noise. As we mentioned above, we are interested in a system that can predict changes in efficiency metrics like APE as small as 0.1%. Hence, if we simulate the noise-free situation, we can get an approximation for the operating margin of our proposed system. Additionally, analog-to-digital conversion is another source of noise to be considered. In our simulations, realistic 12-bit conversion is evaluated.

IV. Results

A sensing system could be designed so that the spectral responses of the sensors can be combined to replicate the spectral response of a PV cell. An example of this approach is shown in Fig. 2. In particular, in this example, the relative heights of the spectral responses of 28 sensors have been adjusted so that the total response of the sensors replicates the spectral sensitivity of an a-Si PV cell. The close similarity between the spectral responsivity of a PV cell and the sum of the correctly weighted output currents from these sensors can then be used to directly estimate PAR for an a-Si PV cell. However, the results in Table I suggest that this method only meets the desired level of accuracy when the SNR is 40 dB or better.

TABLE I
Errors Obtained Using a Direct Method to Calculate the PAR Directly From the Responses of a Set of 28 Equispaced Sensors in Fig. 2

SNR	PAR error (%)
Infinity	0.15
40 dB	0.7
30 dB	1.5

Although conceptually simple, the direct method fails to exploit the correlation between the different parts of the spectrum of natural light. To exploit this correlation, we have investigated the accuracy of a system based upon an optimum set of sensors and the Imai–Berns spectral reconstruction method. This system can be used to estimate the spectrum of light falling on the sensors and the PV cell, which can then be used to estimate PAR and APE. Errors on these metrics can then be calculated as shown in (3). We would expect the mean error to be close to zero, as it actually occurs since errors in this calculation are randomly distributed, with the same probability of being an overestimation or an underestimation. Hence, the standard deviation across the whole dataset is a better error metric for the parameters we study.

Sensor optimization requires an optimization metric. When the spectral estimation system is intended to be used for colorimetric calculations, it is usual to use a combination of spectral and colorimetric metrics in the optimization [11], [12]. However, in our current case, we need the spectral estimates to be as accurate as possible, since we are using that information to later calculate APE and the PAR. We tried to minimize the standard deviation of one of these metrics in our experiments; however, optimizing one metric usually degraded the results obtained for the others. In contrast, we found that minimizing the mean of the spectral root-mean-square error (RMSE) across the whole dataset resulted in very good values for the two error metrics of interest. Moreover, since we want our spectral estimation system to be as general as possible and independent on the PV cell technology and its range of absorption, it is preferable to use a purely spectral metric for the optimization.

In Fig. 3, we show how the error in the APE and PAR decrease as the number of optimum sensors used in our system increases. However, at low noise levels, having just seven optimum sensors is good enough, and little improvement is achieved by adding more sensors to the system.

The set of optimum sensors is very similar for all noise situations (optimum sensors are slightly sharper as noise increases, a very well-known effect [11], [12], [20], [24]). Fig. 4 shows the spectral responses of the seven optimum sensors and the standard reference spectrum ASTM G173-03 [28], which is included in the right axis for convenience. The sensors with higher sensitivities correspond to spectral regions where the irradiance is lower. Each of these spectral responses are wide compared with the spectral resolution of a spectrometer. This means that these data can be gathered without the monochromator, which is an essential part of a spectrometer. Instead, the system can

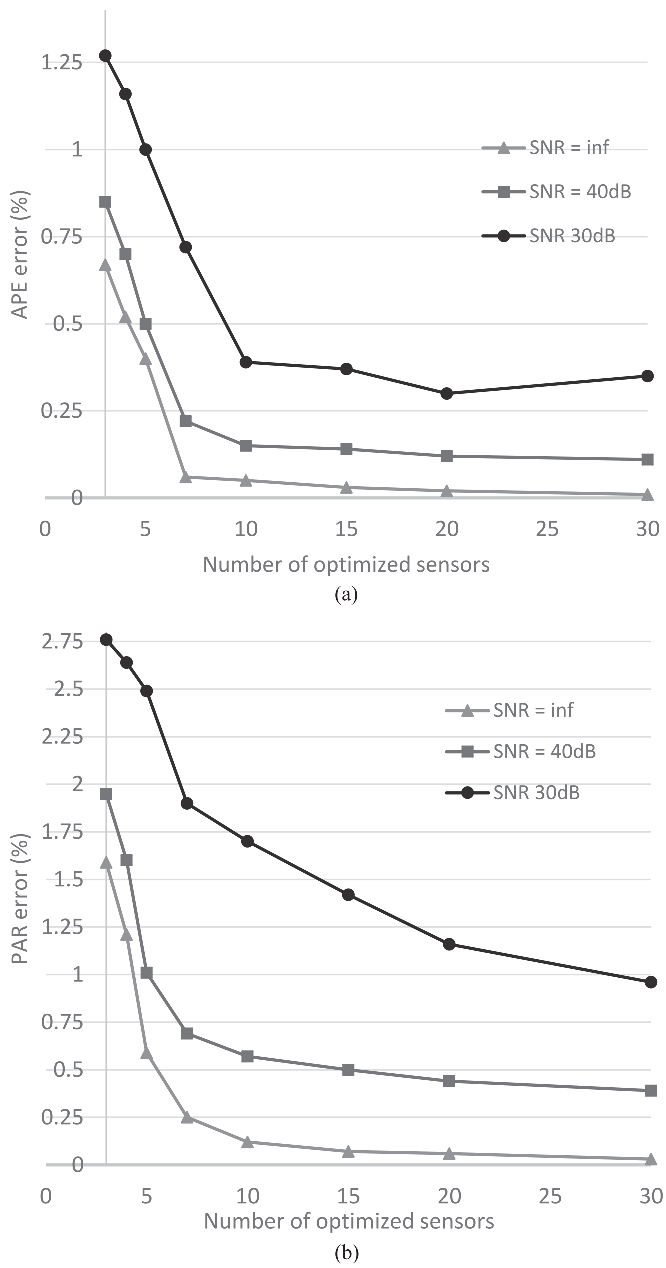

Fig. 3. (a) APE and (b) PAR errors as a function of the number of optimum sensors used for spectral estimation at various noise levels.

be created from a small number of inexpensive photodiodes and filters that cost approximately one tenth of the price of a monochromator.

The set of seven optimum sensors have two important features: First, the set seems spectrally equispaced in order to fully sample the whole range. Second, the relative heights of the sensors are bigger for the extremes of the spectrum in order to compensate for the smaller amount of radiation received in those spectral ranges. Finally, since the metric being optimized in these experiments was the spectral RMSE, which is independent of the PV cell range of absorption, we find some optimum sensors in the spectral range between 800 and 1100 nm, even when the a-Si cells show no absorption in that range.

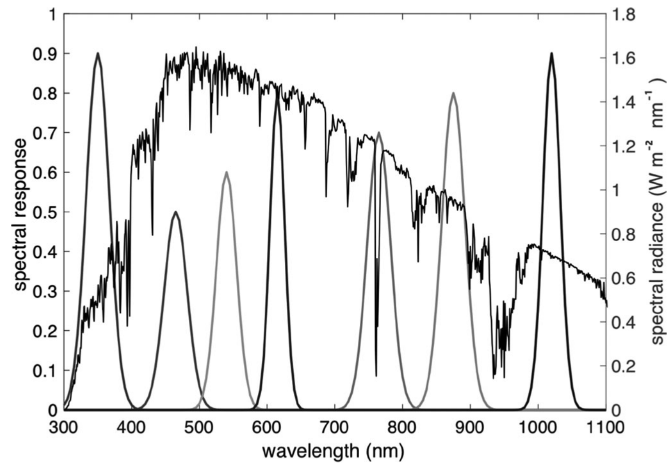

Fig. 4. Spectral responses of an optimum set of seven sensors (left axis) superimposed to the ASTM global tilt reference spectrum (right axis).

V. Conclusion

We have shown that the spectral distribution of the available daylight in Granada is variable enough to have a significant impact on the efficiency of a PV cell. In particular, data gathered over two years showed that the APE, previously used to explain changes in PV cell efficiency, varies significantly throughout a typical day. Having real-time knowledge of the spectrum of the radiation impinging on a PV cell could, therefore, be a useful part of a system that monitors the long-term performance of a cells in a PV system.

We have shown how a potentially inexpensive system, based on a small number of sensors, can be designed in order to provide accurate estimates of APE and/or PAR metrics. The sensor optimization approach is good enough to measure relevant metrics to an accuracy of below 1%. Although they are mathematically complicated, the approaches based on spectral estimation have the advantage of providing more complete information, which could potentially be useful for system diagnostics. Furthermore, optimizing the selection of sensors used for the spectral estimation system significantly improves its accuracy, while reducing its potential cost and enhancing its robustness. The result is a system that is capable of estimating the selected efficiency metrics to an accuracy of better than 1%.

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