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Uncertainty in Photovoltaic Module Energy Rating
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Abstract
Energy rating of PV modules alongside Power rating can facilitate the module technology selection process. However, for module ratings to be comparable, they have to come with a stated uncertainty. This paper proposes a method for estimating this uncertainty, highlighting the importance of investigating and including the correlation between measurements in the overall uncertainty estimate. For the indoor measurement setup at CREST the difference in uncertainty estimate neglecting correlations and accounting for correlations is from 1.3% to 3% respectively (at k=2). Underestimating the uncertainty can lead to a suboptimal selection of PV module technology.

1 Introduction
All PV modules are power rated (in Watts) at Standard Test Conditions (STC: 25°C, 1000W/m2, AM1.5G standard spectrum [1]). It is well known that STC rarely occur as operating conditions in the field. To address this, the IEC 61853 series of standards aim to introduce Energy Rating (ER) in Watt-hours for modules as well as module performance ratio. These involve voltage, current and power rating the modules at a variety of irradiance and temperature conditions, measuring the spectral and angular responses and module temperature relative to the ambient temperature and wind speed. These measurements, with their associated uncertainties, are then intended to be used in combination with standard sets of climatic data with no associated uncertainty for calculating the ER and the module performance ratio. Both of these alongside the STC power rating can then be used to compare technologies and feed into the module selection process. It is clear that to compare between technologies the uncertainty in all three performance indicators has to be considered. Currently only the first part of 61853 is published [2], covering the procedures for power rating at different irradiances and temperatures. Reputable labs have uncertainty estimations for each of those measurement points. This paper addresses the uncertainty of the interpolated points between measurements in an irradiance-vs-temperature matrix and the overall uncertainty in ER (UER). Different measurement setups and procedures will introduce varying levels of correlation between the measurements which affects the uncertainty of the interpolated points and the overall UER. In an indoor setup the random influences are significantly lower compared to the systematic contributors, resulting in mostly correlated measurements. In an outdoor setup they are of comparable magnitude. Three scenarios are considered in this paper: fully correlated measurements, fully independent measurements and measurements with the estimated correlation between indoor measurements at CREST. Monte Carlo simulations are used to generate uncertainty surfaces. A climatic zone typical of the inland UK was generated based on CREST outdoor measurements and used for integrating the overall UER solely due Pmax measurements at various irradiances and temperatures. The uncertainty in spectral and angular response correction as well as the relation between module and ambient temperature measurements are not considered in this work since the standards are not yet finalised and the specific measurements are not fully defined.

2 Uncertainty sources
To calculate a module’s ER, measurements at irradiances varying from 1100W to 200W at temperatures from 15 to 75°C are required. These are specified in [2], where unlikely conditions like 1100W and 15°C module temperature are omitted as shown in Table 1. Points between these measurements and outside the boundaries are bi-linearly interpolated or extrapolated respectively. There are numerous influences that introduce uncertainty in these measurement conditions and thus in the maximum Power measurements (Pmax):
• the uncertainty associated with the Reference Cell (RC) calibration used for setting the irradiance level,
• the irradiance non-homogeneity at the target plane,
• the temperature difference between the device junction and the measured surface (back of module),
• the temperature difference across the module,
• orientation and positional differences between the Device-under-test (DUT) and the RC,
• difference between the solar simulator irradiance distribution and the AM1.5G standard, as well as difference in the spectral responsivity of the DUT and RC (the combination of these is the mismatch factor),
• uncertainties related to the data acquisition system, parameter extraction and curve fitting.

The contribution of each of these sources varies for different measurement setups and is different for each of the points in the irradiance vs. temperature power matrix. The uncertainty sources listed above can be considered independent from each other. The contribution of each of these sources is assessed and quantified individually and an overall uncertainty is calculated according to the JCGM GUM [3]. A summary of the uncertainty estimates at k=1 for the indoor measurements at CREST at the measurement conditions defined in [2] is presented in Table 1 below.

<table>
<thead>
<tr>
<th>Irradiance</th>
<th>15°C</th>
<th>25°C</th>
<th>50°C</th>
<th>75°C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1100W</td>
<td>Na</td>
<td>2%</td>
<td>3%</td>
<td>3.50%</td>
</tr>
<tr>
<td>100W</td>
<td>1.50%</td>
<td>1.30%</td>
<td>2.50%</td>
<td>3%</td>
</tr>
<tr>
<td>800W</td>
<td>2%</td>
<td>1.50%</td>
<td>2.70%</td>
<td>3.20%</td>
</tr>
<tr>
<td>600W</td>
<td>2.20%</td>
<td>1.70%</td>
<td>2.90%</td>
<td>3.40%</td>
</tr>
<tr>
<td>400W</td>
<td>2.20%</td>
<td>1.70%</td>
<td>2.90%</td>
<td>Na</td>
</tr>
<tr>
<td>200W</td>
<td>3%</td>
<td>2.50%</td>
<td>Na</td>
<td>Na</td>
</tr>
<tr>
<td>100W</td>
<td>3.50%</td>
<td>3%</td>
<td>Na</td>
<td>Na</td>
</tr>
</tbody>
</table>

Table 1 Uncertainty table at k=1.

### 3 Correlations in measurements

The major challenge with estimating the $U_{ER}$ is that the assumption that all the measurements in the irradiance-vs-temperature $P_{max}$ matrix are independent does not hold true. For example all measurements are done via setting the irradiance level with the same RC. Any error in the calibration value of that cell would be present in all measurements. Another example is the mismatch factor correction. Often a correction is not applied and is accounted for in the uncertainty estimate of the $P_{max}$ measurement. This results in a systematic error that will bias all measurements in the same direction, even if the unknown value of the correction required is not exactly the same for all measurements. The device-under-test changes its spectral responsivity with temperature and the neutral density filters used for reducing the irradiance of the solar simulator can modify the spectrum, but this change is small relative to the overall mismatch correction required. If a mismatch factor correction is applied, the uncertainty of the correction is still a systematic effect to all measurements, since it would be calculated only once. A detail discussion of the estimation of the correlation between each pair of measurements is outside of the scope of this paper. The general approach involves estimating the uncertainty at STC and then for all other measurement conditions. For a given pair of measurements, each uncertainty component can be classified as systematic across both measurements or random in nature or, as it is most often the case, a combination of both. In the latter case, the uncertainty is separated into two components, one representing the systematic part, e.g. the uncertainty of the RC calibration, and the other random, e.g. any non-linearity of the RC. While for an individual measurement the non-linearity of a RC is an unknown systematic effect, for two measurements at 200W and at 1100W, for example, the uncertainty contribution could be biasing the result in different directions, thus it does not correlate the two measurements. The classification of the nature of the uncertainty component is not only equipment based but also procedure dependent. It must be noted that correlations will be different for every system. The covariance can then be calculated by the sum-of-squares of the systematic contributions present in each pair of measurements. The correlation coefficients are then calculated from the covariance. More details on correlation calculation can be found in [3].

### 4 Energy rating uncertainty

The aim of the paper is to estimate the $U_{ER}$ solely based on the $P_{max}$ measurements at different irradiance and temperatures. The standards for angular and spectral corrections as well as the translation from ambient to back-of-module temperature are not finalised. These measurements are independent from the $P_{max}$ measurement, thus the uncertainties of the correction and temperature translation can be estimated separately and included in the final estimate at a later stage, when the standards are published. However, care must be taken since correlation can be introduced if the same spectral responsivity measurements are used for the calculation of spectral correction and mismatch factor correction. The climatic zones are also not yet published. They however do not carry any uncertainty, thus a climatic zone was created based on irradiance and ambient temperature measured outdoors at CREST. The data was aggregated to hourly values. Since back of the module temperature data was also available for a number of modules, the empirical temperature translation step from ambient to back-of-module temperature was omitted.
Due to complexity, the only practical approach for estimating $U_{ER}$ is to use Monte-Carlo simulations. Since the measurements are not independent, they have to be sampled from a joint probability density function. Therefore, first a multivariate joint probability distribution is created based on the 22 measurements at different irradiances and temperatures, the uncertainty of each measurement and the correlation coefficient estimates for each pair of measurements.

The distribution is defined by 22 expectation values (i.e. the module measurements) and a $22 \times 22$ variance–covariance matrix, where the diagonal of the matrix is the square of the uncertainties of each measurement and the rest of the matrix is the covariance between each pair of measurements. The multivariate distribution was sampled 8000 times creating 8000 sets of 22 simulated measurements of the module $P_{\text{max}}$ at all predefined measurement conditions. Bilinear interpolation and where necessary extrapolation was used to estimate the $P_{\text{max}}$ at the points (irradiance and back-of-module temperature) in the input data set. Finally these were summed to yield the ER of that module. The standard deviation of the 8000 calculated ER of the module is the uncertainty and the mean is the best estimate for the ER. There was no difference in results to two decimal places between simulations with 5000 and 8000 samples or when the simulations were run multiple times. Therefore 8000 Monte Carlo simulations were considered sufficient.

5 Results

For the same module and the defined climatic data based on one year measurements outdoors in Loughborough, the uncertainty of the ER of that module neglecting angular and spectral corrections varied dramatically based on the estimate of the correlation between measurements. If the measurements were fully independent the uncertainty of the energy rating would be as low as 1.32 % at $k=2$ (i.e. with 95% confidence). The normalised uncertainty surface for independent measurements is shown in Figure 1. In the worst-case scenario, where all measurements are considered fully correlated, the $U_{ER}$ was 4.5% at $k=2$. The corresponding uncertainty surface is shown in Figure 2. A simplified estimate of the correlation coefficients of the indoor measurements at CREST is that all pairs of measurements made at the same irradiance conditions have a correlation of 0.6, pairs of measurements made at the same temperature conditions have a correlation coefficient of 0.4 and all other pairs are correlated with each other with a correlation coefficient of 0.3. With these estimates the $U_{ER}$ was 2.96%.

The corresponding uncertainty surface is presented in Figure 3 below.

![Figure 1 Normalised uncertainty surface with independent measurements.](image1)

![Figure 2 Normalised uncertainty surface with fully correlated measurements.](image2)

![Figure 3 Normalised uncertainty surface with estimated correlation between measurements at CREST.](image3)
6 Discussion

The uncertainties of individual indoor measurements at CREST shown in Table 1 are typical for the industry. The uncertainty of $U_{ER}$ for other systems will vary between the fully correlated and independent measurements uncertainties presented here. Clearly, neglecting correlations can result in a considerable underestimation of the overall uncertainty by up to a factor of 3. Based on this analysis it has become clear that for the purpose of ER, realising independent or less correlated measurements is beneficial. This can be done via a mixture of indoor and outdoor measurements, via using a selection of reference cells or a combination of measurements at different institutes.

Realising independent measurements can result in $U_{ER}$ lower than the uncertainties of individual measurements when bilinear interpolation is used. This is because interpolated points can have smaller uncertainties than the measured points as seen in Figure 1. This may seem counterintuitive, but is a limitation of exact deterministic interpolation processes, including bilinear interpolation. Exact means that the predicted surface includes the values of the measured points assuming they have no associated uncertainty. This limitation has been overcome by using the Monte Carlo simulations. Deterministic means that the interpolated values are based on a mathematical formula and do not account for any randomness, there is only one solution to a given set of input values. That means that there is no associated uncertainty due to the interpolation itself and each interpolated point is a weighted average of the points around it. This has been discussed in more detail in [4]. The uncertainty estimation method presented here accounts for the propagation of individual measurement's uncertainty and their correlations into the overall $U_{ER}$ based on the current intention of the PV community to use bilinear interpolation for energy rating calculation. However, exact deterministic interpolation may not be the most appropriate method due to the reasons discussed above. Alternatively, stochastic methods, such as Gaussian process interpolation, that account for randomness can be used for interpolating data with uncertainty [4]. However it requires a pre-defined covariance function. The challenge is in selecting the appropriate covariance function, since those used originally by the Geographic Information Systems community for Kriging (type of Gaussian process) and more recently in the PV community for spatial irradiance interpolation may not be appropriate for use in $U_{ER}$ uncertainty estimation. Investigation of these stochastic methods and into the possible covariance functions is part of our future work.

7 Conclusions

Modules are currently rated in Watts at conditions that are not representative of outdoor operation. The introduction of ER in Watt-hours is an important step in enabling the further growth of the PV industry. However any type of rating is meaningless unless supported by a stated uncertainty. A general method for estimating the uncertainty of ER is proposed in this paper and the importance of estimating the correlations between measurements as well as accounting for them is demonstrated. The analysis shows that for energy rating purposes minimising the correlation between measurements is essential. Since correlations have not been historically of major concern, most setups and procedures will produce highly correlated measurements. Improving the measurement procedures and practices is the first step to minimising correlations and the overall uncertainty in $U_{ER}$. In addition the appropriateness of using bilinear interpolation was discussed, showing that the method results in interpolated points that have smaller uncertainties than the measured points, when the measurements are independent. A stochastic interpolation method could be used instead, however it is not apparent what pre-defined covariance function should be used. A comparison between the two interpolation methods is part of the future work of the authors.

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