UNCERTAINTY CONSIDERATIONS OF INDOOR PV MODULE CALIBRATION BASED ON MONTE CARLO SIMULATIONS

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ABSTRACT: Uncertainties in the calibration of PV devices affect the power rating of modules and thus their value. The expanded measurement uncertainty in P_{max} of modules at state-of-art indoor calibration facilities is between 1.6-3.85% based on conventional Si technologies. The uncertainties of TF technologies are agreed to be higher. The contributions from different uncertainty sources are combined according to the GUM Uncertainty Framework. The Framework has the limitation of considering only the mean and standard deviation of symmetric distributions. This paper advocates the use of the Monte Carlo (MC) method for calculating the overall uncertainty of module calibration that is specific to the device-under-test and the measuring setup. Since the MC method retains all the information from the input quantities, more comprehensive probability density functions can be assigned to the main contributors. Recognised systematic effects can be accounted for by assigning asymmetric distributions to given contributions eliminating the need for correction. The use of the MC method for the total uncertainty calculation allows for a more detailed estimation of the input influences and their understanding and minimisation. In the simulated case study this led to reduction in uncertainty from ±2.5% in I_{sc} to [+1.93%:-1.97%] for a 95% coverage interval.
Keywords: Uncertainty, Monte Carlo, Modules, Calibration

1 INTRODUCTION

Every measurement has an associated uncertainty characterising the dispersion of values that can be attributed to the measurand [1]. A robust uncertainty analysis helps to identify areas for improvement in the measuring setup. All measured PV device performance parameters are subjected to uncertainties. The maximum power (P_{max}) of a PV module is arguably the most important performance characteristic from a commercial point of view. As such, the uncertainty in P_{max} of a module has a direct implication on the price of the device. Typical values of expanded uncertainty (k=2) for indoor measurements of c-Si devices are between 1.6 and 3.85% [2],[3],[4] and somewhat higher for other technologies as confirmed by round-robin results [5],[6]. However, the measurement uncertainty is specific to the measurement system and the devices measured.

The sources of uncertainty for a typical current-voltage solar simulator system are shown in Figure 1.

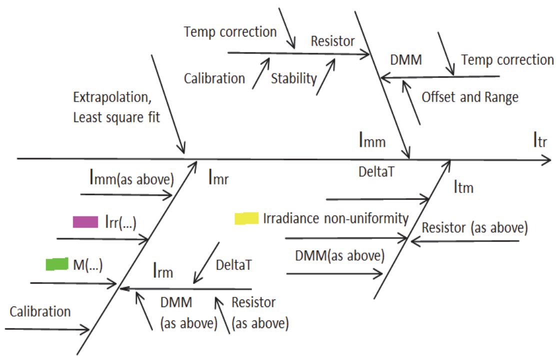

Figure 1: Sources of uncertainty in I_{sc} measurements based on [3]. Main sources of uncertainty are highlighted.

The relative contribution of each source is setup specific. For indoor systems, the light inhomogeneity is a major contributor. Typically, a Type B rectangular distribution is assigned to the non-uniformity with limits depending on the size of the device-under-test and type (size of cells), the reference cell size and the relative position of the two. In most analyses, this represents the worst-case scenario and accounts for a major part of the uncertainty in P_{max}. However making more detailed estimations has little benefit when the ISO 'Guide to the expression of uncertainty in measurement' [7] (GUM) framework is used for the overall uncertainty calculation, as this would not change the final uncertainty. The following section describes the limitations of GUM framework and the available alternative Monte Carlo approach. The paper goes on to describe assigning asymmetric distributions to uncertainty contributors in order to account for identified systematic effects and minimise uncertainty. Since the Monte Carlo method retains all the information from the input distributions, it can be used for a setup and device-under-test specific analysis.

2 GUM UNCERTAINTY FRAMEWORK VS. MONTE CARLO METHOD

The ISO 'Guide to the expression of uncertainty in measurement' prescribes a framework for estimating uncertainty and a method for combining the contributions into an overall uncertainty. In summary, it involves assigning different probability density functions (e.g. Rectangular, Triangular, Trapezoidal) and a range of values to all the contributing influences and approximating them to equivalent Gaussian distributions. Based on a Taylor approximation of the model equations and using the law of propagation of uncertainty these are combined into a single output Gaussian distribution. The standard deviation of that distribution is the measurement uncertainty. There are certain limitations to this method: it does not provide good approximation for non-linear model equations, accounting for correlated sources is difficult and only symmetrical input distributions are allowed. Furthermore, the output distribution is always assumed Gaussian. However, it is possible for one of the contributors to dominate the overall uncertainty. In that case, the output distribution would be very similar to the major contributor and the Gaussian assumption would be invalid.

The Monte Carlo (MC) method is detailed in the GUM Supplement 1 [8] and in [9]. In summary, it involves using pseudo-random numbers to obtain draws of the input values (one from each input distribution). These are run through the model equations and the output value is calculated. Following a large number of runs (typically 10^6 in order to ensure accuracy and convergence of the results) a histogram of the output value defines the probability density function and the uncertainty of the measurement. The advantages of the method are that it can be used easily for correlated and non-linear relations between the inputs and the shapes of the input and output probability density functions are not restricted [10].

Figure 2 shows the same total uncertainty with the same input distributions calculated with both uncertainty propagation methods. For the Monte Carlo simulation the MUSE tool was used [11]. In essence, the MC method validates the GUM approximation in this case. Since the majority of the input distributions are rectangular a small difference can be observed, however the difference in the standard deviation σ is minor. Figure 3 shows the difference for a Class B simulator with 3% inhomogeneity dominating the uncertainty. It can be seen that a Gaussian assumption is questionable in that case.

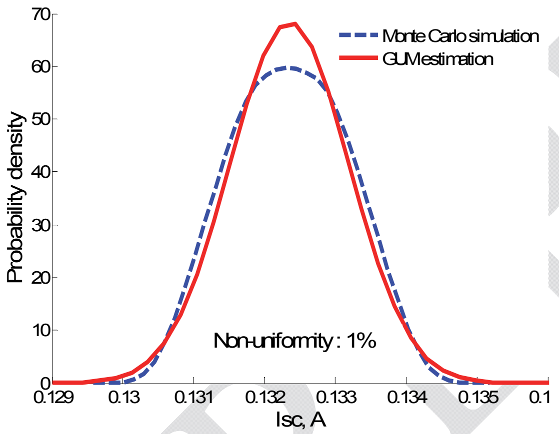

Figure 2: No dominating uncertainty source, the Monte Carlo simulation validates the GUM result.

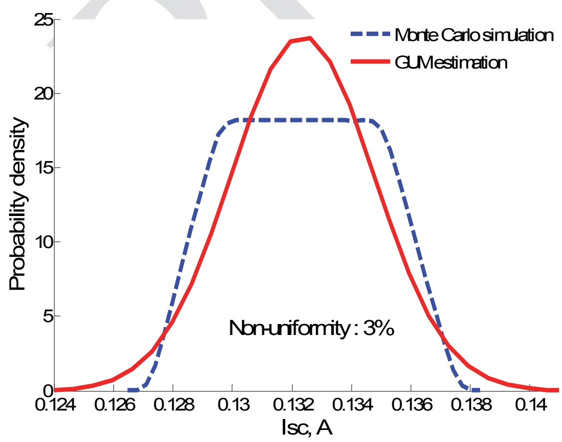

Figure 3: The uncertainty contribution due to the inhomogeneity dominates the total uncertainty and the GUM approximation differs from the Monte Carlo simulation result.

3 MISMATCH FACTOR CORRECTION UNCERTAINTY USING MONTE CARLO METHOD

Field and Emery used the Monte Carlo method for calculating the uncertainty in the mismatch factor correction [12] since it is wavelength dependent and a Type B estimation was difficult if not impossible. Based on those calculations calibration laboratories use empirical methods to assign a Type B uncertainty (e.g. 20 % of the magnitude of the 1-MMF; or 10% of the uncertainty of the SR measurements and Spectral irradiance). Hohl-Ebinger and Warta [13] expanded on that work and calculated the mismatch factor for different combinations of reference cells, devices-under-test and irradiance distributions. They showed that the uncertainty of the mismatch factor is not necessarily proportional to its magnitude. When the reference cell and the device-under-test have regions in the spectral responses that do not overlap, there is no cancelation effect and the uncertainty may be excessively high. They also showed that the wavelengths that introduce the largest uncertainties are the ones corresponding to the peaks in a xenon source. Finally, a red shift of the light source reduced the uncertainty due to the sensitivity of the spectroradiometers used in their setup. This clearly shows the benefit of a device-specific Monte Carlo simulation. The output distribution for the mismatch factor correction uncertainty can be used as the input for the total uncertainty without the need for an approximation and without losing any information.

4 SYSTEMATIC EFFECTS

The GUM Framework allows random and systematic uncertainty components to be treated the same way. This is convenient because the classification can depend on the context. However, in this paper, effects that affect the measurement results in a predictable way and can be corrected for, are considered systematic. In practice, at calibration facilities every effort is made to minimise these. However, when systematic effects require significant resources or are impractical to minimise a correction is made instead. This is the case for the mismatch factor correction. The differences in spectral response between the reference cell and the device-under-test and in spectra between the solar simulator lamp and the AM1.5G result in around ±1% error in the I_{sc} for closely matched devices. The percentage is considerably larger for devices of different technologies without a matched reference cell - as high as 13% [14]. Depending on the facilities the expanded uncertainty of the correction can be as low as 0.4% for cells [3],[4]. Not all systematic effects are so significant and instead of correcting for them, they are accounted for in the uncertainty estimation. An example of this is the difference between the measured temperature at the back of the device and that of the actual junction of the device. In this paper, two uncertainty contributors are considered in more detail: the light inhomogeneity and the temperature deviation across the module.

4.1 Inhomogeneity measurements and systematic effects

Even a Class A simulator can have up to 2% irradiance non-uniformity. The uncertainty contribution due to inhomogeneity is usually estimated as a rectangular distribution with a range equal to the inhomogeneity. The actual uncertainty depends on the size and relative position of the device and reference cell as well as the irradiance map. A device and setup specific analysis mitigates the need for this worst-case assumption. However it requires a map of the irradiance at the target plane. Some labs measure the homogeneity, others model this based on a point source and some just use the manufacturer's specification. If not measured, significant systematic effects are possible. These can be due to lamp adjustment, misalignment in the orientation of the target plane, reflections from frames, floor or the source itself. If measured, the relative uncertainty between measurements has to be low compared to the 2% light inhomogeneity. The number of detectors, their size, orientation, position and temperature as well as noise and digitisation error of the data acquisition all contribute to the uncertainty of the homogeneity measurement. At CREST the homogeneity of pulsed solar simulator used for module measurements is measured with a moving bar with 22 sensors with an area of 1cm^2 and 10cm apart. This horizontal bar is then moved up the measurement plane. The sensors were calibrated both outside in natural sunlight and against a standard source. The relative uncertainty of measurement of the bar at different positions was mainly due to noise. However, the cross calibration uncertainty between sensors was high. The homogeneity measurement was done with the bar oriented vertically and moved across from left to right. This measurement was used for the cross calibration of the sensors. The final results showed an overall inhomogeneity of 1.09% over an area of 180 cm by 200 cm. Small (but larger than the relative measurement uncertainty) systematic effect of more light in the bottom right hand side of the plane was observed as shown in Figure 4. Due to the small non-uniformity, the uncertainty of a correction in I_{sc} measurements of a module would be comparable or higher than the improvement due to the correction itself and thus such a correction is not currently applied to measurements at CREST.

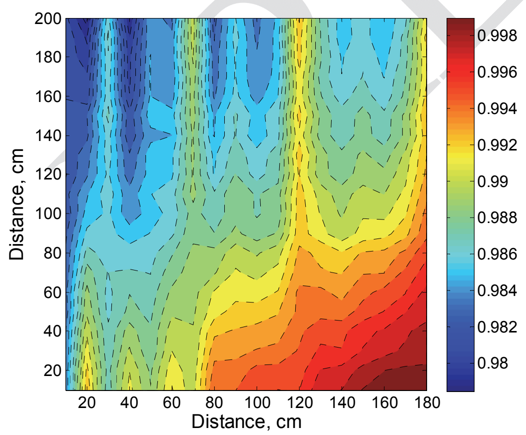

Figure 4: Non-uniformity of the pulsed solar simulator at CREST.

In industry, a homogeneity measurement with low uncertainty and high resolution is likely to be unavailable. However, a systematic effect can be observed and confirmed by changing the position and/or orientation of the device-under-test and reference device. The magnitude of the effect can be quantified, but a correction (which will be device specific) and in particular the uncertainty of the correction would be difficult to estimate.

For a case study, an irradiance plane with vertical gradient in the homogeneity was considered as shown in Figure 5 below.

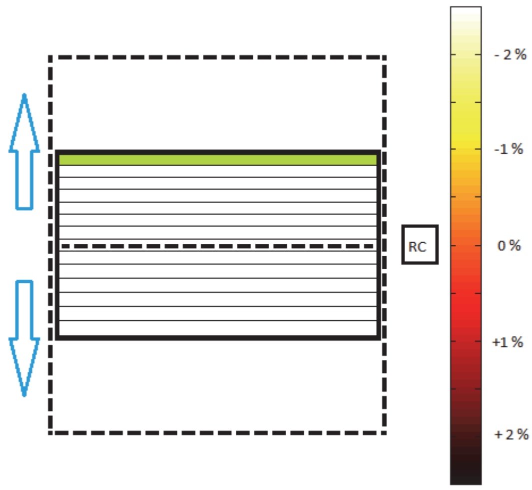

Figure 5: Homogeneity gradient, thin film module orientation, position and limiting cell and reference cell position.

A TF module with cells parallel to the floor will be current limited by the top cell as shown in Figure 5. For the same setup and a different device, this effect may not be significant and the uncertainty could be considerably lower underpinning the need for device type specific uncertainty analysis. Assigning a Type B distribution is based on experience and should represent the best available knowledge about the uncertainty contribution. The probability density function is an interpretation of the existing knowledge. The Monte Carlo method can have any distribution as an input and so an asymmetric one, such as the Weibull or Gamma distributions, can be assigned to represent the effect due to current limiting and homogeneity gradient instead of the worst-case rectangular distribution.

First, the repeatability of measuring at the same position without disconnecting the module has to be considered. Usually there is an irradiance correction integrated into the system to account for the difference in irradiance of the pulse. In addition, the temperature of the room is controlled and thus the repeatability can be better than 0.2%. TF modules experience metastability effects both at millisecond scale and at minutes and hours scale. These affect the absolute results, e.g. due to preconditioning effects during the flash, the measurements are consistently lower. If the appropriate preconditioning procedures for the longer time scale are followed the repeatability between consecutive measurements can still be 0.2%. The pulse duration is assumed to be long enough to negate any capacitive measurement artefacts. The module can be measured at different heights with the reference cell kept at the same place – the middle of the original position of the module. In the case considered, moving the module up would reduce the I_{sc} indicating higher irradiance at the bottom of the irradiance plane and the current limiting cell would be the top one. This means that when measuring the module at the middle the measurements are consistently lower than the true value as shown in Figure 6. Changing the orientation of the module and moving it left to right, can help identify any gradient in the horizontal direction. In this case study for simplicity only a vertical gradient was considered.

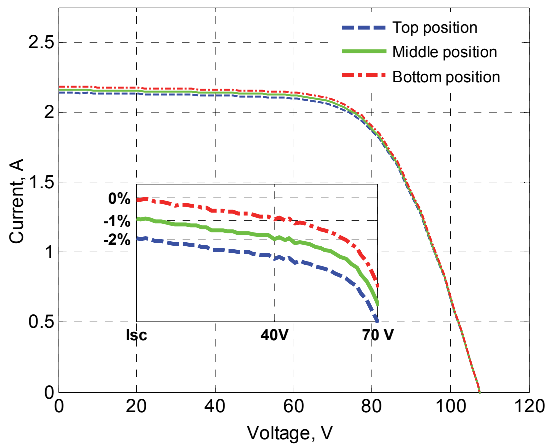

Figure 6: Simulated I-V curves at the different height positions.

Based on these measurements an asymmetrical distribution can be assigned to the inhomogeneity contribution. For the case study a reflection symmetric of a Gamma distribution with α =2 and β = 5 and a rectangular distribution were used as shown in Figure 7.

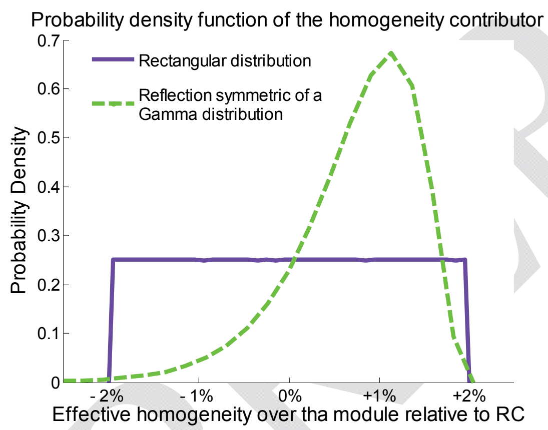

Figure 7: Gamma and Rectangular PDFs of the uncertainty due to non-uniformity

For calculating the overall uncertainty with the Monte Carlo method all identified uncertainty sources were propagated. In particular, the Mismatch factor correction uncertainty was set to 1% and the reference cell calibration value uncertainty to 0.9%. Both stated values are expanded uncertainties of Gaussian distributions. The difference in the overall uncertainty can be seen in Figure 8. For the rectangular distribution, the best estimate was 2.199A and the 95% coverage interval was ±2.5% for I_{sc}. The best estimate with the asymmetrical distribution was shifted to 2.218A and the 95% coverage interval was [+1.93%: - 1.97%]. Assigning an asymmetric distribution to the homogeneity contribution accounted for an observed systematic effect eliminating the need for a separate correction and minimised the overall uncertainty of the measurement. The same approach can be used for systematic effects of a different nature, e.g. more light in the middle of the plane than at the edges. The method can be applied to gradients in both X and Y directions. Any tests that give additional insight into the nature of the systematic effect can be used as the basis for the assigned distribution. Note that this uncertainty calculation is setup and device specific and it will only apply to the same type of devices.

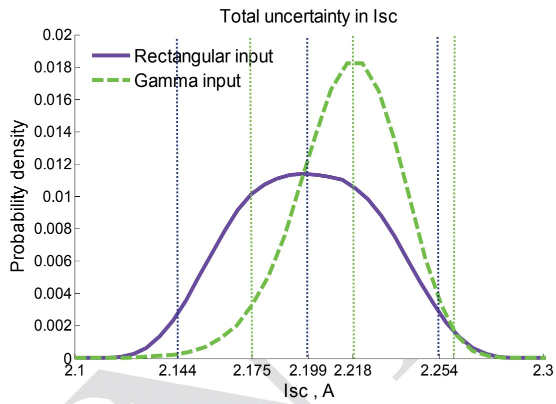

Figure 8: Overall uncertainty in I_{sc} with the two non-uniformity contributions. The vertical lines represent the 95% confidence interval and the highest probability density value.

4.2 Systematic effects in temperature non-uniformity.

Horizontal measurement setups have the disadvantage of a possible temperature gradient at the target plane. At CREST the measurement setup is in a temperature controlled room. The settings of the air-conditioning affect the mixing of the air. In the worst-case scenario, with non-optimal settings, a difference of up to ±1.25 degrees can be observed for large modules. The temperature deviation across a large module can be seen in Figure 9. This is improved by better mixing of the air in the room, but can be minimised further by changing to a vertical setup.

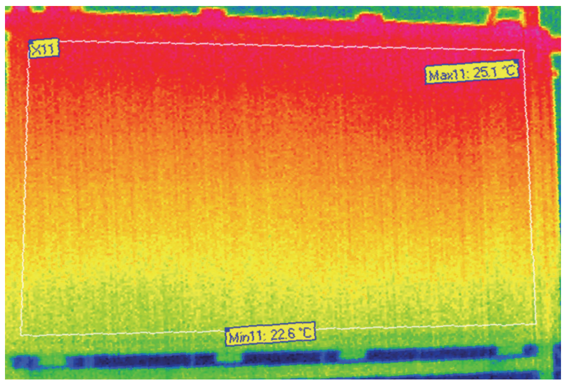

Figure 9: Temperature non-uniformity captured with a thermal camera.

The temperature affects mainly V_{oc} and P_{max}. The orientation of the module as well as the position of the PT100 will affect the uncertainty due to temperature deviation. A typical temperature coefficient for a TF module is between 0.25-0.4%/°C. In this case the uncertainty due to the temperature deviation across the module is the major contributor in Voc total uncertainty accounting for around 60% since the overall uncertainty in Voc is relatively small 0.6% at k=2. Having a map of the temperature across the module such as the one in Figure 9 and a number of sensors at the back can help characterise the temperature deviation across the module and a corresponding asymmetric distribution can be assigned for a device specific uncertainty analysis in a similar manner to the irradiance homogeneity gradient.

5 CONCLUSIONS

The Monte Carlo method for calculating uncertainty contributions propagation to the overall uncertainty of PV device measurements is a powerful technique that allows for in-depth analysis of the influences and can be used to account for systematic effects. It allows for device- and setup-specific analysis that can minimise the overall uncertainty and highlight target areas for improvement of the measurement system. When systematic effects are present but a precise correction difficult, assigning asymmetric distributions that represent the available knowledge can minimise the overall uncertainty. For the simulated case study with 2% irradiance inhomogeneity at the test plane, the uncertainty reduction was from ±2.6% down to [-1.8%:+1.6%] in I_{sc}.

6 AKNOWLEDGEMENTS

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