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Chester Wells
National Renewable Energy Laboratory
Golden, Colorado

National Renewable Energy Laboratory
1617 Cole Boulevard
Golden, Colorado 80401-3393
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MEASUREMENT UNCERTAINTY ANALYSIS TECHNIQUES APPLIED TO PV PERFORMANCE MEASUREMENTS

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INTRODUCTION AND HISTORICAL BACKGROUND

The purpose of this presentation is to provide a brief introduction to measurement uncertainty analysis, outline how it is done, and illustrate uncertainty analysis with examples drawn from the PV field, with particular emphasis toward its use in PV performance measurements.

A number of years ago, Harry Ku of the National Bureau of Standards (NBS), now called the National Institute of Standards and Technology (NIST), stated:

> "The informational content of the statement of uncertainty determines, to a large extent, the worth of the calibrated value." [1]

I believe this statement is equally true for any measurement or final experimental result. The uncertainty information we know and state concerning a PV performance measurement or a module test result determines, to a significant extent, the value and quality of that result.

What is measurement uncertainty analysis? It is an outgrowth of what has commonly been called error analysis. But uncertainty analysis, a more recent development, gives greater insight into measurement processes and tests, experiments, or calibration results. *Uncertainty analysis gives us an estimate of the interval about a measured value or an experiment's final result within which we believe the true value of that quantity will lie.* We will discuss *true value* in a moment.

The methodology for uncertainty analysis imbedded in the standards in use today by a number of groups at NREL was developed largely in the fields of rocket and jet engine testing during the 1960s and 1970s. The history is documented briefly in two papers by Robert Abernethy and others [2,3]. Most details for the methodology can be obtained by using the group of three documents: (1) the Arnold Engineering Development Center report on uncertainty in gas turbine (jet engine) measurements [4,5]; (2) the American Society of Mechanical Engineers standard on measurement uncertainty that is now an American National Standard [6]; and (3) the draft of the International Organization for Standardization (ISO) standard on Fluid Flow Measurement Uncertainty [7].

Abernethy and Ringhiser [2] identified five principal problems that uncertainty analysis addresses:

- Random error uncertainty
- Systematic error uncertainty

- Signed bias limits
- Defined measurement process
- Uncertainty intervals and models

They also identified three areas for future research work in refining uncertainty analysis: calibration curve fitting, weighting competing answers, and outlier methods. One of the additional areas being pursued today is the effect of errors in both X and Y on the uncertainty resulting from curve-fitting.

This analysis method can be applied equally well to the measurement of a single physical quantity, the result of a simple lab experiment, and the intermediate and final results of complex experiments and engineering tests. In addition it can be applied to an entire chain of traceable measurements, starting from an international standard and proceeding through intermediate calibrations to measurements made in a field experiment.

Why should we take the time to perform an uncertainty analysis? A rigorous measurement uncertainty analysis

- Increases the credibility and value of research results
- Allows comparisons of results from different labs
- Helps improve experiment design and identifies where changes are needed to achieve stated objectives (through use of the pre-test analysis)
- Plays a significant role in validating measurements and experimental results, and in demonstrating (through the post-test analysis) that valid data have been acquired
- Reduces the risk of making erroneous decisions
- Demonstrates quality assurance and quality control measures have been accomplished.

I define *Valid Data* as data having known and documented paths of:

- Origin, including theory
- Measurements
- Traceability to measurement standards
- Computations
- Uncertainty analysis of results.

TRUE VALUE: DEFINITION AND IMPORTANCE

Robert Moffat, in an excellent paper entitled "Identifying the True Value - The First Step in Uncertainty Analysis," [8], stated "...almost all situations where uncertainty analysis seems to fail arise because too little attention has been paid to identifying the intended true value of the measurement. Such an identification is always the first step in an uncertainty analysis, and lack of precision in that identification almost always causes serious trouble." In my experience, I have repeatedly found this to be true. The ability to define exactly what is being sought in a measurement process or a final result saves time, money, confusion, and frustration.

By true value, I mean the value of that quantity sought through the measurement and experimental process, whether it is a directly observable phenomenon (e.g., the dc power out of a specific PV array on a 20° south-facing tilt at solar noon on June 22, 1992, at NREL's Outdoor Test Facility into a specified resistive load) or one that exists only as a concept (e.g., the average efficiency of a certain model of PV array measured on June 22 at normal incidence over the range of air masses from 2.0 to 3.5).

The true value is the value of the quantity that would result if it could be measured perfectly; it can also be the final result of a "perfect" experiment, having no error in stating the true value sought, no measurement errors in carrying out the experiment, and no errors added in data reduction and interpretation processes. The true value is unknowable because of our finite measurement limitations and the fact that our measurement sensors frequently disturb that which we are trying to measure (even if we could define the true value without error). We can only approximate the true value, however close we may approach it.

A significant source of error in measurements and tests may arise from lack of agreement on definitions, such as in the definition of "area" for a PV cell, module, or array. Even thought the other measurements were performed with totally negligible error, disagreement on the definition and measurement of the area can lead to differences in results from lab to lab ranging from 1% to as great as even 200%. [9] I would call this an example of gross errors, arising from failure to adequately define (or agree on) the true value.

The ANSI/ASME standard (ANSI/ASME PTC 19.1-1985 [6]) partially covers defining the true value by stating that the assumptions inherent in performing a measurement uncertainty analysis include specifying the test objectives.

ERROR, UNCERTAINTY, AND THE TRUE VALUE

All measurements have errors - the differences between the measured values and the true value we are trying to achieve. But as discussed above, we don't really know the true value (it is really unknowable), so the actual amount of error in each measurement is uncertain. The purpose of measurement uncertainty analysis is to achieve a good quantitative estimate of the limit of those errors and thereby be reasonably confident that we can define the interval about our measurement result within which we expect the true value to lie.

In order to analyze the uncertainties, we must understand the nature of measurement errors and how to assess the errors in our measurements and experimental results. Three types of errors are encountered in a measurement process: random errors, systematic errors, and gross errors.

Random (also called precision) errors are the most commonly recognized and analyzed type of errors. Their effects are observed as varying results (scatter) in repeated measurements of the same unvarying quantity (if our measurement system has sufficient resolution). We are not talking about varying measurement results caused by variations in the quantity we are measuring (e.g., constantly changing values of the solar irradiance). A truly random measurement process will produce a distribution of results that will yield a frequency distribution that has a Gaussian, or so-called normal, distribution. The random error component is characterized by the shape of the distribution function and the standard deviation of the measurements about the mean value. The mean value of those measurements is usually given as result of the measurement process. A number of sources contribute random errors to an experiment's result. Widely known statistical techniques are used to arrive at the random error component in an uncertainty analysis of a final result. How to combine all of the random errors is part of the methodology of uncertainty analysis.

However, the mean value is almost surely offset by an unknown amount from the true value--we won't know how much or in which direction. The difference between the mean value and the true value is called the systematic (bias or offset) error. Systematic errors do not produce scatter in the final result, so they are not detected through statistical techniques. The exact values of systematic errors are unknowable, but we must still attempt to assess how large they might be. To do so requires considerable knowledge about the experiment, the measurement processes and instrumentation used, plus making some educated and seasoned engineering judgments. That is what makes systematic errors so difficult to identify and quantify. They are often ignored, or it is even said they don't exist. Some authors believe they are caused only by mistakes or equipment failure, or that they have been totally removed by calibration [10], so that they are either overlooked or believed to be negligible. There are likely quite a few sources of systematic error in any but the most simple and trivial measurement. Combining the various systematic errors is another portion of the methodology of uncertainty analysis, as are the methods of combining both random and system errors into a final total uncertainty statement.

Often, the systematic component of the total uncertainty is larger than the random component. Five types of systematic or bias errors are identified in Table 1.

The systematic errors having a known sign and magnitude (type 1) are reduced to a size limited by our measurement processes. We remove these through the calibration process. However, even in the best calibration processes, including those at the National Institute of Standards and Technology, there are still some residual uncertainties remaining. These need to be identified and accounted for in our uncertainty analysis, even if they can be shown to be small enough to have a truly negligible effect on the final result.

The small systematic errors (types 2, 4, 5) are also to be identified and accounted for in the uncertainty analysis, as appropriate.

Five Types of Systematic or Bias Error			
	Known Sign and Magnitude	Unknown Magnitude	
Large	(1) Calibrated Out	(3) Assumed to be Eliminated	
Small	(2) Small or Negligible;	(4) Unknown Sign	(5) Known Sign
	Contributes to Bias Limit	Contribute to Bias Limit	

Table 1. Types of Systematic or Bias Errors [Ref. 4 or 5, p. 2]

A bias limit is defined as an estimate of the maximum possible systematic or bias error that could exist. The bias error, ß, of a particular measurement will lie between the two bias limits, **B**:

-B ≤ ß ≤ +B

Gross errors are the large errors of unknown magnitude that have been assumed to be eliminated but, in fact, have not (type 3). These errors invalidate the uncertainty analysis process and the experimental result. Outlier analysis techniques may find some of them but will not necessarily always detect them, especially when they never change (are truly systematic). How to find them or work to prove that they do not exist is a topic that Peter Stein addresses in detail in his courses (see the Resources section of this paper).

THE MEASUREMENT UNCERTAINTY MODEL

The following sections will present only a brief overview of the methodology of uncertainty analysis that is the basis of the ANSI/ASME PTC 19.1-1985 standard. For more complete discussions, refer especially to references 3 or 4, 5, and 6.

Measurement uncertainty is a function of the specific measurement process used to obtain a measurement result, whether it is a simple or complex process. Measurement uncertainty analysis provides an estimate of the largest error that may reasonably be expected for the specific measurement process. If you change the measurement process, then the uncertainty analysis must be re-examined and changed as appropriate. Errors larger than the stated uncertainty should rarely occur in actual laboratory or field measurements, if the uncertainty analysis has been performed correctly.

The random component of uncertainty for an individual measurement is taken as $\pm 2\mathbf{S}$ (or $\pm t_{95}\mathbf{S}$ for small samples of data, 30 or fewer measurements) where **S** is the standard deviation of the individual measurements and t_{95} is the two-tailed "student's t" value for a 95% confidence level. The individual random error components are added in quadrature to develop the overall random uncertainty component.

The individual systematic error components are added in quadrature to obtain the systematic uncertainty component, the bias limit, **B**.

Commonly, one of two models of uncertainty is used to combine the random and systematic uncertainties to develop the quantitative estimate of the uncertainty interval about the final result within which the true value is believed to lie. The interval is formed from the combination of the two components (random and systematic), added linearly or in quadrature. The two models follow:

- **U_{99} = U_{ADD}** - Should contain 99% of all measurement or experiment results if repeated many times.

$$U_{99} = B + 2 \cdot S \quad or$$

$$U_{99} = B + t_{95} \cdot S$$

- **U_{95} = U_{RSS}** - Should contain 95% of all measurement or experiment results if repeated many times.

$$U_{95} = \sqrt{B^2 + (2 \cdot S)^2}$$

U_{99} is a more conservative estimate of the uncertainty interval and will always be larger than **U_{95}**.

FUNDAMENTALS OF HOW TO DO UNCERTAINTY ANALYSIS

We will now outline the steps for performing a measurement uncertainty analysis. For the details, consult references 4 (or 5), 6, 7, and 8. Reference 6 is the U.S. national standard we use at NREL for uncertainty analysis.

Step 1: Clearly define the "true value" sought, in writing. It is well worth the time to do this in writing, for it will keep before you what you are trying to measure and will help clarify the measurement process and the experiment goal [8].

Step 2: List every possible elemental source of measurement error that can be thought of, no matter what the source or how large or small the error may be thought to be.

Step 3: Group the error into these three categories, by source: (1) calibration errors; (2) installation and data acquisition errors; and (3) data reduction errors.

Calibration errors are those associated with the calibration of each measuring instrument, sensor, transducer, etc. Installation errors are those errors that arise from how sensors are installed for the experiment. Be particularly alert here for systematic errors. Data acquisition errors are those associated with the performance of the data acquisition system (including sensors) in the environment in which it is used. Use manufacturer's specifications if you have no better data and you have reason to believe you trust those specs. Gross errors frequently arise in the installation and data acquisition processes. Data reduction errors are errors associated with the computer's algorithms, errors encountered in curve-fitting resulting experiment data. I prefer to assign calibration curve fitting errors to the calibration category, not the data reduction category. I want to know how much uncertainty originates in the calibration process and deal with it there, if necessary.

Step 4: Classify the errors into systematic and random errors. If data exist from which a standard deviation can be calculated, consider it a random error. Manufacturer's specifications can give useful information for the pre-test analysis. Random errors produce scatter in the final result. Otherwise, consider the errors to be systematic errors.

Step 5: Separately propagate the two types of error to the final result. Use the Taylor series or small deltas ("dithering") to determine the sensitivity of the final result to each individual source of error. Simply adding the errors may lead to an uncertainty estimate that is too large or too small, depending on the sensitivity coefficients for each error. This is discussed in detail in the references.

For random errors, the uncertainty is:

$$S = t_{95}\sqrt{\sum_{i=1}^{n}\left(\frac{\partial F(X_1,\ X_2,\ ..X_n)}{\partial X_i}\cdot S_i\right)^2}\ ;\quad S_i=\frac{s_i}{\sqrt{N_i}}$$

where t_{95} is the two-tailed "student's t" for 95% confidence limits (use 2 if the number of measurements averaged is 30 or more), F is the function from which to compute the final result, the Xs are the independent variables, and $\partial F/\partial X_i$ is the sensitivity coefficient of $\mathbf{S}_i$. If the value of X_i is the group mean of M groups of N measurements, S_i is the standard deviation of the means of the M groups of measurements of the variable X_i, and s_i is the standard deviation of the individual measurements that form the mean of the N measurements.

For the systematic errors, the uncertainty is given by the following equation, where $\mathbf{B}_i$ is the bias limit for variable i, and $\partial F/\partial X_i$ is the sensitivity coefficient for $\mathbf{B}_i$.

$$B = \sqrt{\sum_{i=1}^{n}\left(\frac{\partial F(X_1, X_2, \ldots X_n)}{\partial X_i} \cdot B_i\right)^2}$$

An important caution: be careful not to mix percentage and absolute errors (percent added to watts/meter^2, for example)!

Step 6: Calculate the uncertainty interval using either model (or both): $\mathbf{U_{99}}$ or $\mathbf{U_{95}}$.

Step 7: Use pretest and post test analyses. The use of both tests reduces the cost and risk of performing useless experiments, publishing invalid data, drawing wrong conclusions, or making wrong decisions. Uncertainty analysis should be factored into decisions, such as those concerning awards for PV cell, module, or system performance.

Use the pretest analysis to predict the uncertainty before an experiment or test is performed. This can determine the appropriateness of measurement instruments and techniques before the investment is made in actually procuring equipment and running the proposed experiment. If the predicted uncertainty is not small enough to obtain the needed result, redesign the experiment—don't go on!

Use a post test analysis to examine the final results for validity, problems, and the necessity of repeating the experiment. Uncertainty information for the final report is obtained in the post test analysis.

Step 8: In the final report, show the final random error component of the uncertainty together with the associated degrees of freedom, the bias limit, and the uncertainty model used ($\mathbf{U_{99}}$ and/or $\mathbf{U_{95}}$).

The degrees of freedom, df, in the final result arising from the various random error sources are computed using the Welch-Satterthwaite equation. If df is more than 30, then use 2.0 instead of t_{95}. See the references.

SOME EXAMPLES OF UNCERTAINTY ANALYSIS

First, several examples will be drawn from the photovoltaics field to illustrate how uncertainty analysis has been or can be used.

In a paper believed to be the first complete uncertainty analysis of PV reference cell efficiency measurements [11], Emery, Osterwald, and I tried to include all sources of systematic and random errors associated with that measurement process. A total uncertainty of ±1.0% was shown to be possible *if all sources of systematic error were minimized*. A more typical value of ±7% was shown to be expected if some common sources of error were neglected. In a typical case, the uncertainty for systematic errors were found to be five times as large as that for random errors. This demonstrates that using only the repeatability (standard deviation) to estimate the uncertainty in an efficiency measurement would greatly underestimate the actual error.

That paper also discussed a hypothetical example that demonstrates the value of knowing and minimizing the uncertainty of a measurement process. The example concerned measuring device performance improvements, during which the magnitudes of the improvements are assumed to decrease during the development of the device. After six improvement in the steps, a ±5% uncertainty measurement process is unable to confidently resolve smaller improvements, whereas the ±1% measurement process can resolve the magnitude of the progress through nine improvements.

This ability to resolve small changes is important, whether the goal is to measure research device improvements or device degradation. Uncertainty analysis gives us the insight to determine what size changes we should expect to confidently resolve and what changes "will be lost in the noise" of the measurement process. This is especially important information if we are measuring experimental devices that are degraded by exposure to light during the measurement process.

Emery and others at SERI (now NREL) examined the uncertainties of a variety of methods used to calibrate PV reference cells [12]. Many sources of error in the various primary and secondary calibration methods were identified and discussed. The total uncertainty for the various methods was developed, allowing comparisons with each other and with air-mass-zero (AM0) calibrations. It was noted that systematic errors were larger by 15% to 400% than the random errors in all methods except one. Again, true systematic errors cannot be reduced by repeated measurements, and they are not related to the standard deviation of a calibration data set. Table 2 shows the summary table from that paper.

Calibration Method	E_{tot}	Bias (±%)	Random (±%)	Total (±%)
Global fixed tilt	pyranometer	3.1	1.5	4.3
Global fixed tilt	direct + diffuse	2.3	1.2	3.2
Global-normal	pyranometer	2.5	1.5	3.7
Global-normal	direct + diffuse	0.8	1.2	2.5
Direct-normal	cavity radiometer	0.5	0.3	0.7
X25 simulator	±1% reference cell	1.0	0.2	1.1
SPI-SUN simulator	±1% reference cell	1.4	1.2	3.0
AM0 (JPL balloon calibration)†		0.5	0.2	0.7
AM0 (NASA airplane calibration)†		1.0	--	1.0
† A standard uncertainty analysis has not been performed for AM0 calibration methods; these are estimates based on published information.				

Table 2. Summary of PV calibration uncertainties [12]

The table clearly shows that the best method to calibrate PV reference cells from the ground is against an absolute cavity radiometer in the direct-normal mode, and that the best method to transfer that calibration to another reference cell is to use an X25 solar simulator. The other methods do not rival these, except those made outside the atmosphere, for which a rigorous uncertainty analysis was not performed in the manner we are describing in this paper.

Daryl Myers examined the uncertainties encountered in acquiring field data included in the SERI solar spectral radiation data base [13]. He listed the major sources of uncertainty evaluated, identifying the systematic and random errors and the total uncertainty for the calibration process and the field measurements with the spectroradiometers. This information was shown as a function of wavelength. Many measurement processes have uncertainties that are a function of wavelength, amplitude, frequency, range, etc., so it is valuable to show such dependencies.

The uncertainties encountered in calibrating thermopile type pyranometers and pyrheliometers at NREL were listed in quite some detail in a technical report by Daryl Myers [14]. This report provided the beginning point for establishing a formal uncertainty analysis for our calibration of these radiometers. Its extensive lists of elemental error sources can give insight for PV device testing as well. When changes in the measurement process or refined knowledge becomes available, then the uncertainty estimates can be improved.

A PV DEVICE EFFICIENCY TEST EXAMPLE

When we consider the uncertainties that may be encountered during the outdoor electrical characterization of a PV module or array, the efficiency of the unit will be of major interest. If the efficiency, η, is defined as the ratio of power out, P_O, to power in, P_I, we can perform a pre-test analysis for a hypothetical measurement system designed to measure that efficiency. Such an analysis can give us insight into how well we might measure the efficiency, as well as the major sources of uncertainty.

$$\eta = \frac{P_O}{P_I}$$

To get the sensitivity of η to both P_O and P_I, partial derivatives are taken:

$$\frac{\partial \eta}{\partial P_O} = \frac{1}{P_I} = \Theta_O$$

$$\frac{\partial \eta}{\partial P_I} = -\frac{P_O}{P_I^2} = \Theta_I$$

where η = efficiency, P_O = power out, P_I = power in, and
Θ_O, Θ_I = sensitivity coefficients for P_O and P_I.

For the random component of uncertainty,

$$S_\eta = \sqrt{(\Theta_O \times S_O)^2 + (\Theta_I \times S_I)^2}$$

$$S_\eta = \sqrt{\left(\frac{1}{P_I} \cdot S_O\right)^2 + \left(-\frac{P_O}{P_I^2} \cdot S_I\right)^2}$$

$$S_\eta = \sqrt{\left(\frac{1}{P_I} \cdot S_O\right)^2 + \eta^2\left(\frac{1}{P_I} \cdot S_I\right)^2}$$

If S_O is negligible, then

$$S_\eta = \sqrt{\eta^2\left(\frac{S_I}{P_I}\right)^2} = \eta\left(\frac{S_I}{P_I}\right) \quad or, \quad \frac{S_\eta}{\eta} = \frac{S_I}{P_I}$$

That is, the relative random error for the efficiency is the same as that for the input power.

Similarly for the systematic (bias) error,

$$B_\eta = \sqrt{(\Theta_O \times B_O)^2 + (\Theta_I \times B_I)^2}$$

$$B_\eta = \sqrt{\left(\frac{1}{P_I} \cdot B_O\right)^2 + \left(-\frac{P_O}{P_I^2} \cdot B_I\right)^2}$$

$$B_\eta = \sqrt{\left(\frac{1}{P_I}\cdot B_O\right)^2 + \eta^2\left(\frac{1}{P_I}\cdot B_I\right)^2}$$

If B_O is negligible, then

$$B_\eta = \sqrt{\eta^2\left(\frac{B_I}{P_I}\right)^2} = \eta\left(\frac{B_I}{P_I}\right); \quad or, \quad \frac{B_\eta}{\eta} = \frac{B_I}{P_I}$$

The total uncertainty in the efficiency is

$$U_{99} = \pm(B_\eta + t_{95}\cdot S_\eta)$$

or,

$$U_{95} = \pm\sqrt{B_\eta^{\,2} + (t_{95}S_\eta)^2}$$

Now we will work with some numbers for a very simplified hypothetical example: consider a PV array system having a defined total area of 10-m² (five 1-m X 2-m, 20 V 10 A modules, series-connected), operating at normal incidence to the sun with a global normal solar irradiance of 1.1 kW/m² and producing a total direct-current (DC) output power of 1 kW (100 V, 10 A). Efficiency is to be measured at the conditions prevailing at the time the measurements are taken without corrections for spectral mismatch, module temperature, ambient air temperature or wind speed, or other conditions not addressed in this simplistic examples.

These are the specifications used:

- "Area" for the array is taken as the sum of the total area of five 1-m X 2-m module areas, measured with a systematic error of 1-mm/1-m and a random error (1σ) of 1-mm on either the length or width of a module. The sides are straight and perpendicular.

- The 1.100 kW/m² solar irradiance is measured with a pyranometer that was calibrated on the horizontal, resulting in a calibration factor (CF) of 10.00 mV output per 1 kW/m². An additional ±0.8% systematic error component is interpreted for the direct normal CF (zenith angle = 0°) from calibration data plots. An additional systematic error component of ±1% is added to account for the temperature coefficient of the response of the pyranometer and the departure from an ideal cosine response, and ±0.5% random error is added, based on data available from the calibration process. The non-symmetrical nature of these biases has been ignored for simplicity's scale.

- The pyranometer output voltage is measured with a digital multimeter (DMM) on the 120.000 mV range (stated accuracy is ±0.02% of reading + 10 μV).

- The PV 100-V output voltage is measured with a DMM on the 120.000 V range (±0.01% of reading + 5 mV).

- The 10-A output current is sensed by measuring the 100-mV drop with a DMM (same 120-mV range specification as above) across a 10-mΩ (±0.1% systematic error) shunt resistor.

No errors have been added for the following:

- misalignment of the measurement plane of the five PV modules relative to that of the pyranometer

- lack of a perfect plane for each PV module

- differences in the diffuse irradiance impinging on the pranometer and on the PV modules due to non-uniform foreground horizons, reflections from objects in the field of view, etc.

Such a simplistic measurement of efficiency would not be adequate for evaluation of this array's performance or degradation as a function of a variety of parameters, including time, or for purposes of a rigorous efficiency rating or a comparison with other arrays measured at other times, even in the same setup.

If a rigorous measurement of efficiency of a PV array or module is to be conducted, referenced to standard conditions, then all of the factors above should be considered plus others, such as

- the error in measuring and correcting for the cells temperature in the array or module (the cells are not directly accessible, nor is the cell temperature uniform across the module), and

- the error in measuring the spectra and computing the spectral mismatch factor.

The results are summarized in the table in Table 3.

PV SYSTEM EFFICIENCY MEASUREMENT ($\eta = P_O/P_I$)	System-atic	Random ($\pm 1\sigma$)	Total (U_{95})
Power Out (DC Volts X Amps):			
Volts	0.01%	0.0025%	0.011%
Amps (incl 10mΩ shunt)	0.12%	0.005%	0.12%
P_{OUT} (B_O, S_O)	0.12% 1.2 W	0.0056% 0.056 W	0.12% 1.2 W
Power In (Area X Irradiance):			
Area	0.20%	0.11%	0.30%*
Irradiance Calibration: Pyranometer Calibr. (Hor.): Use on Direct Normal:	 3.0% 0.8%	 0.82% --	 3.51%*
Irradiance Measurement: Added for TempCo, Cosine, Solar Variability, etc.: Voltage Measurement:	 1.0% 0.02%	 0.5% 0.045%	 1.41%
P_{IN} (B_I, S_I) [**B_I** includes "*fossilized" values]	3.65% 402 W	0.50% 55W	3.8% 416 W
Ratio ($\eta \approx$ 0.09091) Using Sensitivity Equations:	**B_η** = 0.00333 = 3.66%	S_η = 0.000455 = 0.50%	**U_{95}** = 0.00344 = 3.8% **U_{99}**=4.2%

Table 3. Summary of hypothetical PV system efficiency measurements.

The concept of "fossilization" is introduced in Table 3. For example, the CF for the pyranometer has both systematic and random errors associated with it. But once that single CF value is derived and used, there is no scatter produced by it in the final result. Therefore, the total uncertainty is used as a systematic error factor in the irradiance measurements acquired using the pyranometer with the fixed value for CF. In other words, the CF does not vary and the random component of uncertainty in the calibration is a fixed (fossilized) part of the total uncertainty.

The conclusion to be drawn is that the total uncertainty in this very simple example of the measurement of efficiency is nearly entirely bound to the uncertainty of measuring the solar irradiance, which is limited by the performance and uncertainty in calibrating the pyranometer. Calibration of the pyranometer on the tilt can reduce the uncertainty if it is to be used on the tilt for global normal measurements. Many of us have believed this for some time. This example is offered to help us pursue a better understanding of outdoor efficiency tests.

Measurement of the global normal irradiance could be improved significantly by using a pyrheliometer (Normal Incidence Pyrheliometer/NIP), or, ideally, an absolute cavity radiometer to measure the direct beam, and a pyranometer with a tracking shading disk to measure the diffuse radiation in the plane of the array. This could possibly reduce the irradiance measurement uncertainty to half or less of what is shown here.

We see that we can identify the sources of uncertainty and deal with them until we achieve a satisfactory level of uncertainty in our results—or can recognize when we have reached the limit of our ability to measure efficiency.

System characterization, including improvements or degradation, cannot be measured to better than the measurement uncertainties encountered in the experimental process. Much more could be said about methods of improving the design of experiments using just the equipment specified in the hypothetical case above. Some ideas are imbedded in details in references 4 or 5, 6, and 7.

Charles Babbage, inventor of the first calculating machine, is supposed to have said, "Errors using inadequate data are much less than those using no data." A similar comment is in order concerning uncertainty analysis: "An uncertainty analysis based on inadequate information is better than no uncertainty analysis at all." This is not intended to encourage superficial work, but we can start with a somewhat simplistic analysis to begin to gain the insight and rigor we need.

SUMMARY

We have seen that measurement uncertainty analysis goes beyond simple error analysis. It develops a carefully defined estimate of the interval about the measurement or experiment final result within which the true value of the quantity sought is expected to lie. Uncertainty analysis is vital for understanding calibration, measurement, and experimental processes and final results. It utilizes our best knowledge in statistics and engineering.

The methods for combining random and systematic errors, and obtaining final uncertainty intervals, have been carefully researched and documented in the U.S. national standard, ANSI/ASME PTC 19.1-1985.

Several useful examples have been shown for the application of uncertainty analysis to PV applications, including PV efficiency measurements. Resources for acquiring a more detailed understanding of the subject will now be discused.

RESOURCES FOR KNOWLEDGE ABOUT UNCERTAINTY ANALYSIS

There are a number of resources available from which to learn the details of measurement uncertainty analysis. The books and reports cited in the references provide a good starting point. I recommend that a person really wanting to learn the subject take one of the courses taught by Ron Dieck or Robert Abernethy as early as possible. Additional resources are listed below, including references [15, 16, 17] that are not referred to above.

Measurement Uncertainty and Related Courses:

- "Measurement Uncertainty: Concepts and Applications" - Taught as a 3-day on-site course and a 2-day Instrument Society of America (ISA) course by Ronald H. Dieck; emphasizes systematic uncertainty. Contact: Ron Dieck Associates; 7 Dunbar Road, Palm Beach Gardens, FL 33418 (uses References 6 and 15, plus extensive notes and handouts).

- "Test Measurement Accuracy" - A measurement uncertainty course with emphasis on systematic errors, taught by Robert Abernethy as a 2-day on-site course and for American Society of Mechanical Engineers (ASME), ISA, and the University of Tennessee Space Institute. Contact: Robert B. Abernethy; 536 Oyster Road, North Palm Beach, FL 33408 (uses References 4 and 6, plus extensive notes and handouts).

- "Measurement Uncertainty--Measurement Assurance" - A 5-day course taught by Rolf B. F. Schumacher; emphasizes random error and metrology applications; does not emphasize ANSI/ASME PTC 19.1-1985. Contact: Coast Quality Metrology Systems, Inc.; 35 Vista del Ponto, San Clemente, CA 92672-3122 (uses extensive course notebook).

- "Measurement Uncertainty Training Course" - A introductory 4-day course taught by Al Catland; especially good for senior technicians, but does not follow exactly ANSI/ASME PTC 19-1-1985. Contact: Measurement Technology Company; 12620 Avenida De Espuela, Poway, CA 92064-2535 (uses extensive course notebook).

- "Measurement Systems Engineering and Dynamics Courses" - Detailed engineering level on measurement systems, per se; highly insightful; two consecutive 5-day courses organized by Peter Stein; generally taught in March each year; also given in on-site versions. Contact: Stein Engineering Services, Inc.; 5602 East Monte Rosa, Phoenix, AZ 85018-4646 (uses extensive course notebook and handouts).

- "Designing and Specifying Data Acquisition Systems" - A 2-day course taught by James L. Taylor for ISA (Course #T330) emphasizing uncertainty goals as a design criteria. Contact: Instrument Society of America; 67 Alexander Drive, P.O. Box 12277, Research Triangle Park, NC 27709 (uses Ref. 16).

Technical Paper Sessions:

The following meetings almost always have at least one session devoted to uncertainty analysis, plus possible tutorials or short courses on this and related subjects.

- ISA International Instrumentation Symposium (April or May each year).

- Measurement Science Conference (January or February each year).

- National Conference of Standards Laboratories Annual Workshop & Symposium (July or August each year).

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