Uncertainty Estimation for Instrumentation in Electronics and Optoelectronics

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Abstract— This paper presents an overview of uncertainty estimation methodologies applied to advanced instrumentation in electronics and optoelectronics, with emphasis on phase-noise metrology, microwave photonics, and Brillouin spectroscopy. The study examines uncertainty evaluation procedures for complex measurement systems, including phase-detector-based phase-noise analyzers, optoelectronic oscillators, and scanning tandem Fabry-Pérot interferometers. Major uncertainty contributors such as thermal fluctuations, calibration limitations, detector nonlinearities, environmental perturbations, and signal-processing effects are analyzed within the framework of the Guide to the Expression of Uncertainty in Measurement (GUM). Particular attention is devoted to the propagation of uncertainties in nonlinear and multi-domain photonic-electronic systems, combining optical, microwave, thermal, and computational effects. Practical approaches for uncertainty budgeting, calibration traceability, and long-term stability assessment are discussed. The paper also highlights the importance of international comparisons for ensuring global consistency and traceability in modern metrology. Future challenges associated with emerging ultra-low-noise and integrated photonic instrumentation are finally addressed.

Keywords—Measurement Uncertainty; International Comparisons; Uncertainty analysis; Errors in Electronics; Microwave Photonics; Optoelectronic oscillator

I. INTRODUCTION

The continuous development of advanced electronic and optoelectronic instrumentation has led to increasingly demanding requirements in terms of precision, traceability, and reliability of measurements. In modern metrology systems [1], uncertainty evaluation has become a fundamental component not only for validating experimental results but also for ensuring comparability among laboratories and industrial measurement platforms worldwide. This paper presents an overview of uncertainty estimation methodologies applied to instrumentation systems in electronics and optoelectronics, with emphasis on phase noise metrology, microwave photonics, and Brillouin spectroscopy measurements. The work is based on several recent studies devoted to the rigorous analysis of measurement uncertainty in complex optoelectronic systems. Particular attention is given to phase noise characterization techniques using phase-detector-based measurement systems and optoelectronic oscillators operating in the microwave domain. These systems are highly sensitive to multiple uncertainty contributors including thermal fluctuations, detector nonlinearities, calibration limitations, frequency drift, environmental perturbations, and data acquisition instabilities. The paper discusses practical approaches for identifying dominant uncertainty sources and for propagating uncertainties according to the framework established in the Guide to the Expression of Uncertainty in Measurement (GUM) [2]. A significant part of the discussion focuses on uncertainty evaluation in scanning tandem Fabry-Pérot interferometer measurements used for Brillouin frequency shift characterization [3,4]. Such measurements are particularly relevant for material science, optical fiber sensing, and microwave photonics applications. The influence of spectral fitting procedures, instrumental linewidth, scanning nonlinearity, and signal-to-noise ratio on the final uncertainty budget is analyzed. The presented methodology demonstrates how reliable uncertainty estimation contributes directly to improving the reproducibility and credibility of experimental observations. The paper also highlights the broader role of international comparisons in maintaining consistency within the global metrology infrastructure [5]. Comparisons between national metrology institutes (NMIs) and research laboratories are essential for establishing confidence in measurement capabilities and ensuring traceability across different technological domains. The relationship between uncertainty analysis and international equivalence of measurements is examined through recent developments in electronic and photonic metrology. Beyond the theoretical aspects, practical recommendations are proposed for implementing uncertainty estimation procedures in laboratory instrumentation systems. Strategies for uncertainty budgeting, calibration chain optimization, statistical treatment of repeated measurements, and long-term stability assessment are discussed.

The paper emphasizes that uncertainty evaluation should not be considered as a final administrative step of experimentation, but rather as an integral part of instrument design, measurement strategy, and data interpretation. Finally, perspectives are provided on future challenges associated with emerging high-frequency and photonic instrumentation, including ultra-low phase noise oscillators, integrated microwave photonics, and AI-assisted measurement systems. As instrumentation performance continues to improve, uncertainty analysis will remain central to guaranteeing the reliability, interoperability, and scientific validity of next-generation electronic and optoelectronic measurements.

II. MEASUREMENT SYSTEMS AND METHODOLOGY

In this section, we introduce the methodology we apply. We first look at Phase noise systems, then at the Fabry-Perot interferometer, and then at optoelectronics.

Phase noise systems:

Phase noise is a measure of the short-term random fluctuations in the phase of a signal generated by oscillators,

synthesizers, or communication systems. In the frequency domain, it appears as spectral spreading around the carrier frequency and is usually expressed in dBc/Hz at a given offset frequency from the carrier. Phase noise is important because it degrades signal purity, increases bit error rate in communication systems, and limits the performance of radar, clocking, and frequency synthesis applications. The phase-noise power spectral density is commonly defined as $L(f) = 10log_{10}\left(\frac{P_{noise}}{P_{carrier}}\right)$, where the noise power is measured in a 1Hz bandwidth at an offset frequency f. Phase noise is a frequency domain representation of short-term phase instabilities of a signal. Phase noise is typically described as a single sideband (SSB) phase noise and denoted as *L(f)*. Note phase noise has been redefined as half of the power spectral density of phase fluctuations $L(f) = S_\phi(f)/2$. Another important relation links the signal to phase fluctuations: $\upsilon(t)=A\cos(2\pi f_0 t + \phi(t))$, where $\phi(t)$ represents the random phase variations. Oscillator quality factor Q, thermal noise, and device flicker noise are the main contributors affecting phase-noise performance in electronic systems [6].

Fabry-Perot interferometer:

Fabry-Perot interferometer is an optical instrument used to study light through multiple beam interference [7]. It consists of two highly reflective, parallel mirrors separated by a small distance, allowing light waves to bounce repeatedly between them. As the reflected beams combine, they create interference patterns that depend on wavelength and mirror spacing. This device is widely used in spectroscopy, telecommunications, astronomy, and laser technology because it can measure extremely small differences in wavelength with high precision [3]. Scientists employ Fabry-Perot interferometers to analyze atomic spectra, determine refractive indices, and improve optical filters. Their ability to produce sharp transmission peaks makes them valuable for applications requiring accurate and sensitive measurements of light. The instrument remains essential in modern physics and photonics research worldwide.

Optoelectronic oscillator (OEO) instrumentation:

OEOs are key devices in modern metrology, optical communications, and advanced sensor systems because they generate ultra-low phase-noise microwave signals through the combination of optical delay lines, electro-optic modulators, and feedback loops. The ability to derive high-purity microwave signals from optical systems [7] is particularly important in metrology, where such signals are used in applications such as interferometric distance measurement, frequency references, and time-resolved sensing. In this context, the study presented in Reference [8], which evaluates the phase-noise uncertainty of a 10.52 GHz OEO, is especially noteworthy because earlier work rarely addressed the metrological analysis of OEO performance with the same level of depth and rigor. Authors concentrates on several critical aspects of the system's behavior and measurement methodology. First, they identify the dominant noise mechanisms affecting the oscillator, noting that noise can arise from multiple sources including the laser, modulator non-linearity, fiber dispersion, electronic amplifiers, temperature drift, and the feedback loop itself, and that understanding the interactions between these elements requires expertise in both optical and microwave engineering. Second, they develop a comprehensive uncertainty budget for phase-noise measurements, recognizing that a phase-noise spectrum contains multiple frequency offsets, each associated with different physical noise processes such as flicker noise, thermal noise, or cavity-related effects, and that estimating the uncertainty of these contributions requires a hybrid methodology that combines measurement statistics, electronic characterization, and system identification. Third, the study places strong emphasis on long-term stability, demonstrating that environmental control, thermal stabilization, and mechanical isolation are essential factors, as long-duration measurements reveal how environmental variations propagate through the system and ultimately contribute to measurement uncertainty. Finally, the work contributes to the broader effort toward standardization in photonic microwave generation by proposing an uncertainty model that supports the development of best metrological practices in a field where technical standards and norms are still evolving, thereby reinforcing the idea that expert-driven uncertainty estimation is not merely a statistical exercise but rather a detailed physical investigation into the behavior of a complex photonic-electronic system.

III. Uncertainty Evaluation Procedures

In this section, we need to address several points that are necessary for uncertainty analysis. After clearly defining what we are trying to evaluate in terms of uncertainty, we must define the two major categories of uncertainty terms, but also refer to an internationally adopted reference guide in order to have a unified perspective for the systematic treatment of complex processes. We also need to address Propagation Models, as well as Calibration and traceability.

The quest for the true value:

But to begin the uncertainty evaluation procedures, we need to recall what we are looking for when we perform a series of measurements. We would like to know where is the true value knowing the measured value, then provide an uncertainty. Figure 1 illustrates what we want to find out.

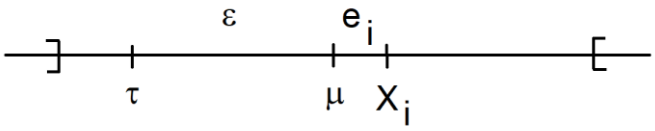

Fig. 1. This figure illustrates the problem of the uncertainty estimation. τ is the true value we are searching for; μ is the result of the measure (1 … n shots); X_i is the result of the ith measurement; ε is the systematic error; e_i is the error of precision.

Type A / type B uncertainties:

Type A and Type B uncertainties are two categories used to evaluate measurement uncertainty. In type A measurement uncertainty assessments, it is generally assumed that the distribution best describing an input quantity, given repeated independently measured values of that quantity, is a Gaussian distribution. So, type A uncertainty is determined through statistical analysis of repeated observations. It reflects random effects in measurements and is commonly expressed using standard deviation or variance. In contrast, Type B uncertainty

is evaluated using scientific judgment and other available information, such as calibration certificates, manufacturer specifications, previous measurement data, or environmental influences. For a type B uncertainty assessment, the only information available is usually that the value sought lies within a specified interval, for example [a, b]. In this case, knowledge of the quantity can be characterized by a rectangular probability distribution [2] with limits a and b. While type A relies on experimental repetition, type B depends on knowledge and experience about the measurement system. Both types are expressed as standard uncertainties and combined to estimate the overall uncertainty of a measurement result. Their distinction is fundamental in metrology because it ensures a consistent and transparent evaluation of measurement reliability and comparability.

Guide to the Expression of Uncertainty in Measurement (GUM) methodology:

The GUM [1] provides an internationally accepted framework for evaluating and expressing measurement uncertainty. Its methodology begins by defining the measurement model, which relates the measurand to all input quantities influencing the result. Each input quantity is assigned a standard uncertainty obtained through either Type A or Type B evaluation. The GUM approach then combines these standard uncertainties using the law of propagation of uncertainty to obtain a combined standard uncertainty. When necessary, an expanded uncertainty is calculated by multiplying the combined uncertainty by a coverage factor, typically corresponding to a specified confidence level. The methodology emphasizes traceability, transparency, and consistency in reporting measurement results. Widely applied in science, engineering, and calibration laboratories, the GUM ensures that measurement results can be compared reliably across institutions, industries, and international borders.

Propagation models:

Propagation models describe how uncertainties associated with input quantities influence the uncertainty of a final measurement result. These models are based on mathematical relationships connecting measured variables to the measurand. In uncertainty analysis, propagation is commonly performed using the law of propagation of uncertainty, which combines the standard uncertainties of all input quantities while considering their sensitivities and possible correlations. Sensitivity coefficients quantify how strongly each variable affects the final result. For simple linear systems, uncertainty propagation can be calculated analytically using partial derivatives. However, for complex or nonlinear systems, numerical approaches such as Monte Carlo simulations [9] are often preferred because they provide more accurate representations of probability distributions and correlations. Propagation models are essential in experimental science, calibration, engineering, and quality assurance because they identify dominant sources of uncertainty and improve measurement reliability. Their application enables laboratories and industries to quantify confidence in measurement results and to comply with international standards for uncertainty evaluation and reporting. Accurate propagation analysis also supports decision-making in research, manufacturing, and regulatory assessments.

Calibration and traceability:

Calibration is the process of comparing a measuring instrument with a reference standard of known accuracy in order to determine and correct measurement deviations. It ensures that instruments provide reliable and accurate results within specified limits. Traceability refers to the property whereby a measurement result can be linked to national or international standards through an unbroken chain of calibrations, each contributing to measurement uncertainty. Together, calibration and traceability form the foundation of measurement confidence and comparability. They are essential in scientific research, industrial production, healthcare, and regulatory compliance because they guarantee consistency, reproducibility, and international acceptance of measurement results and testing procedures.

IV. Representative Results and Discussion

In this part, we will introduce the notion of elementary uncertainty terms, then, through two examples relating to the determination of these terms for a power or a phase noise level, illustrate how among several contributions, it can happen that one of the elementary uncertainty terms becomes predominant.

We express uncertainty elementary terms in decibels or in percentage. Method underlines the critical importance of uncertainty quantification and international comparability for Power as well as frequency, paving the way for robust, traceable, and globally consistent way of uncertainty analysis.

Analysis of the results on the elementary uncertainty terms on a power level:

Through a first example, calibrating power meters allows us to realize that certain terms can take precedence over others when estimating uncertainty [10].

TABLE I. Elementary terms for power estimation

Elementary uncertainty terms	**Contribution**
	expressed in %
1.1. Calibration certificate	2 [a]
1.2. Drift	0.1
1.3. Interpolation	0.2
2.1. Power on standard	0.5
2.2. Power on unknown arm	0.5
2.3. Ration of power on lateral arm	0.1
3.1. Mismatch	0.5+ 6Γ
3.2.Repeatability of connectors	0.3
3.3. Instabilities of generators	0.05

[a] Calibration certificate is the major contribution here.

We perform calibration by direct comparison of the unknown wattmeter relatively to a known bolometer. In this example of elementary terms contribution illustrated in Table I, we have elementary uncertainty terms of three categories: calibration (1.i), measurement means (2.i) and other components (3.i), with i=1…3. In this case, the contribution of the values given by the calibration certificates is preponderant regardless of efforts to reduce the contribution of other elementary uncertainty terms. Mismatch is also an important elementary term as any variation impacts the global uncertainty.

Analysis of the results on the elementary uncertainty terms on the phase noise of a radio frequency signal:

Second example is on phase noise measurement uncertainty analysis on radio frequency or microwave devices, according to the method used [11] by F. Walls et al, we can then refer to the determination, based on the classical method for the uncertainty analysis at 0.001-1.6 GHz for frequency offsets from 1 Hz to 100 kHz at the National Metrology Institute (NMI) of Singapore [12]. For this phase noise elementary terms determination, we find out that the major contribution is related to the reference source phase noise as we get from Table II. Similarly, as the previous example, the contribution of one of the elementary uncertainty terms is also preponderant.

TABLE II. ELEMENTARY TERMS FOR THE PHASE NOISE OF A SIGNAL GENERATOR AT 640 MHZ FOR FREQUENCY OFFSET FROM 1 HZ TO 100 KHZ

Elementary uncertainty terms	**Contribution**
	expressed in dB
System noise floor	0.0003
Reference source phase noise	1.23 [b]
Phase conversion factor	0,053
Frequency response	0,029
Linearity	0,050
Resolution bandwidth switching	0,17
Relative amplitude	0,40
Temperature variation	0,034
Repeatability of connectors	0,30

[b] Reference source phase noise is the major contribution here.

For both of those two examples discussed above, elementary terms are given at 1σ, equivalent to 68.27% for a normal distribution in statistics, with σ being the standard deviation. For metrology applications, as it is not enough to ensure an acceptable coverage of the statistic distribution, final uncertainty is defined at 2σ, according to the empirical rule of 95.45% at 2σ being more efficient for a normal distribution in statistics. On the other hand, when we are required to work on industrial processes in electronics, it is common practice to switch to 6σ due to the need to cover a better acceptance rate for industrial electronic components. Six Sigma (6σ) is a set of techniques and tools for process improvement, introduced by *Motorola* in 1986 [13]. At 6σ, the normal distribution is approximatively of 1 in a billion. It is easy to understand the importance of the reproducibility of electronic components during manufacturing processes in factories. The 6σ method is not only used for determining uncertainties. This method is a management method aimed at pushing quality assurance systems to their possible limits. However, a meta-analysis published in 2014 and covering the 1995-2013 period, identified numerous failure factors, up to 34, common to 56 articles [14].

It is also interesting to note that the tool for determining measurement uncertainties may not be used in the same way when considering an application in the industrial electronics sector. For example, it has been observed that research laboratories working upstream of development projects sometimes provide measurement uncertainties that are a little too optimistic. NMIs are extremely rigorous and are based on the methodology recommended by the Guide to the Expression of Uncertainty in Measurement. On the other hand, manufacturers, for reasons of legal precautionary principle, have an interest in reducing their uncertainties by proposing, for example, a legally binding uncertainty accompanied by a typical uncertainty that is closer to reality. These aspects are discussed in the literature [5]. During intercomparison campaigns [15], it is possible to note the difference in the level of uncertainty given between these three categories of participants: academic research laboratories, NMIs, and industrialists.

To ensure greater confidence in the results of uncertainty calculations, comparisons between the different NMIs have been regularly organized for almost a century. The first international comparison of time and frequency standards was coordinated by the Bureau of Weights and Measures, abbreviated BIPM from the French *Bureau International des Poids et Mesures*, and reported at the 7th *Conférence Générale des Poids et Mesures* (CGPM) in 1927 [16]: the General Conference on Weights and Measures, abbreviated CGPM from the French: *Conférence générale des poids et mesures* is the supreme authority of the BIPM. Measurement uncertainty is commonly evaluated using the Guide to the Expression of Uncertainty in Measurement (GUM), which is currently being revised to address modern methods and digital metrology [17,18]. So-called modern methods are continually being developed. And when the metrology community considers that the time has come to formally adopt them, as with normative aspects, the guide describing the method for calculating uncertainties may also evolve.

Additionally, it is necessary to remember that nothing is fixed; the very substance of conceiving what uncertainty is is a living concept. Debate continues over the relationship between measurement error and uncertainty, as well as the conceptual meaning of measurement itself [19,20].

Metrology is undergoing a profound transformation [5] due to the rapid evolution of photonic instrumentation and techniques. Following comparisons on phase noise of microwave oscillators [15], optical frequency combs [21], ultra-stable lasers [22], Brillouin-based systems [3], whispering-gallery resonators [23], Fabry-Pérot interferometers [24], microwave sources [25], bulk acoustic wave resonators [26], high-purity microwave generation [27], and new classes of hybrid optoelectronic oscillators [28] now form the backbone of high-precision measurement infrastructures. These advances allow resolutions on fractional frequency stabilities better than 10^{-16}, opening unprecedented scientific and industrial opportunities. These exceptional capabilities also bring high sensitivity to perturbations, coupling effects, and complex error sources, creating major metrological challenges. A key issue is evaluating uncertainties in non-linear, multi-domain systems combining optical, electronic, thermal, mechanical, and computational components. Maintaining long-term stability and traceability is equally difficult, as temperature drifts, mechanical instabilities, and laser fluctuations can strongly affect performance. Comparability between laboratories must also be ensured despite varying techniques and standards. In addition, emerging electronic and photonic technologies evolve faster than standardization procedures, while reduced uncertainty budgets require increasingly precise modelling of subtle physical effects. Our work addresses these challenges through rigorous theory, systematic experiments, and participation in

international comparison initiatives to improve reliable precision measurement science.

V. Conclusion and perspectives

Uncertainty estimation has become an essential component of modern instrumentation in electronics and optoelectronics, particularly as measurement systems reach increasingly high levels of precision and complexity. This paper has reviewed the principal methodologies used to evaluate uncertainty in phase-noise metrology, microwave photonics, optoelectronic oscillators, and Brillouin spectroscopy systems. The discussion demonstrated that uncertainty analysis is not limited to statistical post-processing, but rather constitutes a fundamental element of instrument design, calibration strategy, data interpretation, and long-term measurement reliability. The presented examples show that advanced photonic and electronic systems are influenced by numerous uncertainty contributors, including thermal effects, environmental perturbations, nonlinearities, frequency instabilities, detector limitations, and signal-processing imperfections. Applying the principles of the Guide to the Expression of Uncertainty in Measurement (GUM), together with Type A and Type B evaluations, uncertainty propagation models, and calibration traceability, enables rigorous and transparent quantification of measurement confidence. Such methodologies are indispensable for ensuring reproducibility, comparability between laboratories, and international acceptance of measurement results. The role of international comparisons has also been emphasized as a cornerstone of global metrology infrastructure. As emerging technologies increasingly combine optical, microwave, electronic, thermal, and computational domains, maintaining equivalence between measurement systems becomes more challenging and more important. Ultra-stable lasers, optical frequency combs, integrated microwave photonics, and hybrid optoelectronic oscillators now operate at performance levels where extremely small perturbations can significantly affect uncertainty budgets.

Future developments in instrumentation will require even more sophisticated uncertainty models capable of addressing nonlinear interactions, multi-physics coupling, and large datasets generated by automated measurement platforms. Artificial intelligence and advanced numerical methods may assist in uncertainty evaluation, anomaly detection, and adaptive calibration procedures. Artificial intelligence also brings new possibilities which, in the long run, may lead to a review and evolution of modern methods of uncertainty analysis. This is already being applied in the medical field to quantify uncertainty in Internet of Medical Things [29] and to increase the level of trust in the decision-making process [30], in decision analysis through learning [31] as well as in industrial applications, for example on turbines uncertainty analysis [32,33]. With artificial intelligence, the metrology community now has powerful tools for assessing uncertainties in decision support. It is also already possible to rely on methods such as Deep Learning, and not only in the field of robotics [34]. Nevertheless, rigorous physical understanding and metrological traceability will remain indispensable foundations of reliable measurement science. Continued collaboration between laboratories, international organizations, and industrial partners will therefore be essential to support the next generation of high-precision electronic and optoelectronic instrumentation.

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