# Approaches to Evaluate the Virtual Instrumentation Measurement Uncertainties

Salvatore Nuccio and Ciro Spataro

***Abstract*—This paper deals with the metrological characterization of virtual instruments. After a brief description of the features, the components and the working principle of the virtual instruments and the various uncertainty sources are analyzed. Then, two methods to evaluate the uncertainty of the measurement results are presented: a numerical method simulating the physical process of the A/D conversion, and an approximated theoretical method applying the "uncertainty propagation law" of the "guide to the expression of uncertainty in measurement." With both methods, the combined standard uncertainty of the measurement result is obtained, starting from the standard uncertainty generated by each single source. The results obtained by means of the theoretical analysis are compared with the ones obtained from numerical simulation and with the ones obtained by means of experimental tests.**

***Index Terms*—Digital signal processing, uncertainty estimation, virtual instruments.**

## I. Introduction

In THE last few years, the term Virtual Instrument (VI) has extensively entered the measurement and instrumentation language, in particular, in the industrial environment.

The VIs are "real" instruments since they are able to capture and process data arising from phenomena in the real world. These instruments are "virtual" in the sense that some aspects of their operations are implemented in software. Even if the modern "conventional" instruments also utilize more and more software, the VIs can be distinguished because they make use of a general-purpose computer, which can also carry out a variety of other tasks by loading other software.

There are many definitions of VI; in the following we report the National Physical Laboratory definition [1]: "A Virtual Instrument is a reusable measurement instrument created by adding hardware and software to a general purpose computer, and which uses a computer screen to provide the visual interface to the instrument."

Their working principle is very easy to describe: the physical quantity is transduced in the electric signal which is conditioned to be adapted to the successive circuits. The signal is sampled at a frequency at least twice its bandwidth and converted to numerical codes. The acquired samples are processed by the suitable measurement digital signal processing block, usually developed by the user, to obtain the measurement results which are displayed in a virtual panel of the PC monitor.

A typical VI is constituted of the following blocks (Fig. 1):

- transducers and signal conditioning accessories (transformers, attenuators and amplifiers, anti-aliasing filter, multiplexer, and so on);
- data acquisition board with sampler, A/D converters, and clock generator;
- general-purpose computer (e.g., PC);
- software (data acquisition board control, digital signal processing, and user interface).

For correct employment in a quality management system, it is essential to characterize these instruments and to estimate the uncertainties associated with the measurement results [2]. The uncertainty evaluation must be an economically acceptable process, so the evaluation method has to be, even if approximate, easy to apply. With this aim, many authors have dealt with this topic, trying to provide a methodical procedure, but without applying the rules of the ISO-Guide to the Expression of Uncertainty in Measurement (GUM) [3]. We already applied an approximated theoretical approach to a particular instrument (a flickermeter) [4], [5]. Starting from the particular considerations we made about that specific instrument, we tried to carry out a more systematic treatment, strictly following the procedures described in the GUM. Therefore, in this paper, we present this theoretical methodology, in the hope it could be useful to assess the uncertainties associated with the generic VI. Moreover, we propose a new numerical approach, which, by using an *ad hoc* developed software tool, permits evaluation of the measurement uncertainties, overcoming the possible inapplicability of the pure theoretical method.

So, in the following, we deal with the identification of the uncertainty sources, which give a contribution to the uncertainty of the measurement result, and we also deal with the evaluation of the standard uncertainties, associated with each source (Section II). In Section III, we analyze how the uncertainties of each acquired sample combine and propagate through the processing algorithms, which, in turn, are uncertainty sources. In Section IV, we apply the proposed uncertainty evaluation procedures to a realized virtual instrument and we verify experimentally the proposed methods.

## II. Sources of Uncertainty

In this context, we do not consider the errors due to transducers and conditioning accessories. Even if these errors are often predominant compared to the uncertainties generated in the A/D conversion, the transducers and conditioning accessories variety is so wide that it is necessary to analyze separately each particular situation. On the contrary, it is possible to carry out a general treatment in the case of the A/D conversion process.

In regard to this process, the main uncertainty sources are (Fig. 2): pre-gain offset and its temperature drift, gain and its temperature drift, long-term stability and temperature drift of the onboard calibration reference, integral nonlinearity, post-gain

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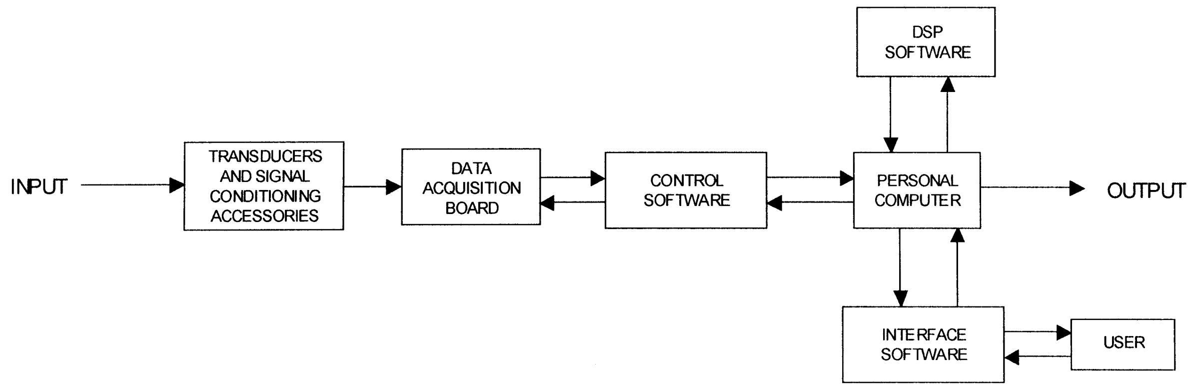


Fig. 1. Block diagram of a virtual instrument.

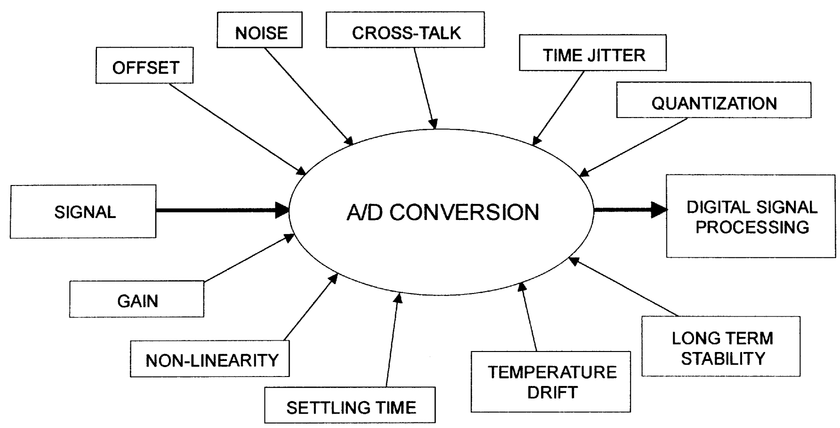


Fig. 2. Uncertainty sources of the A/D conversion process.

offset and its temperature drift, noise, cross-talk, settling time, time jitter, quantization, and differential nonlinearity [6]–[8].

To characterize the data acquisition boards, some parameters regarding the overall behavior of the boards, such as the effective number of bits, are often used. But these parameters are not always present in the manufacturers' specifications, so to obtain them, it is necessary to carry out expensive and laborious tests. They are measured for conventional signals (usually sinusoidal), so they do not have validity for any other signal. Moreover, they do not take into account some uncertainty sources such as offset and gain. If accurately determined, these parameters are useful to characterize the good quality of a data acquisition board, whereas they lose their validity when it is necessary to evaluate the VI actual measurement uncertainty. For this purpose, it is our opinion that the starting point must be evaluating the standard uncertainties associated with each uncertainty source. It can be carried out by means of statistical methods with a Type A evaluation according to the GUM (but we need a statistically sufficient number of VIs of the same kind), or it is also possible to use manufacturers' specifications (Type B evaluation). An uncertainty evaluation starting from the manufacturers' specifications is, of course, less expensive and less time consuming, since it does not require any kind of test.

For the offset, gain, temperature drift, long-term stability and nonlinearity errors, the manufacturers declare an interval $\pm a$ where the error surely lies. According to the GUM, provided that there is no contradictory information, each input quantity deviation has to be considered equally probable to lie anywhere within the interval given by the specification, that is modeled by a rectangular probability distribution. The best estimate of the uncertainty is then $u = a/\sqrt{3}$. If there is reason to suppose that the values nearest to the mean are more probable, it is possible to hypothesize a normal distribution with a 99.73% confidence interval equal to $2a$. In this case, the best estimate of uncertainties is $u = a/3$. It is possible to do a compromise, adopting a triangular distribution, for which the best estimate of the uncertainty is $u = a/\sqrt{6}$. From our point of view, in some cases, a U-shaped distribution could be adopted (with the values nearest to the mean less probable); actually, if the error is on average much smaller than the upper limits, the instrument could be classified in a higher class by the manufacturer and easily sold at a higher price. In these cases the best estimate of the uncertainty is $u = a/\sqrt{2}$. The quantization error is usually considered to be uniformly lying within an interval of 1 LSB, so the best estimate of the standard uncertainty is $1/\sqrt{12}$ LSB. The standard uncertainty related to noise can be directly obtained from the technical specifications, since it is usually expressed as rms value. The cross-talk errors are produced by the interference in the multi-channel acquisition. Its related uncertainty is expressed as the minimum ratio between the signal rms value and the interference signal rms value. The settling time is the amount of time required for a signal that is amplified to reach a certain accuracy and stay within the specified range of accuracy. The manufacturer declares this range for the maximum sampling rate and for the full-scale step, but the errors on the measured signal depend on the actual sampling rate and on the actual signal step. The impact of time jitter uncertainties of the measuring chain is being transformed on the signal uncertainty as a function of signal derivatives. For the worst case, it is possible to use the following expression [9]

$$u_{jitter} = 2^{-(\log_2(2/\sqrt{3}\,\pi f_x \tau_\alpha)-1)} \cdot V_{range} \tag{1}$$

where $\tau_\alpha$ is the rms aperture jitter and $f_x$ is the maximum frequency component of the signal.

All of these uncertainties can be considered not correlated, so the standard uncertainty of each acquired sample can be calculated as the root sum square of the standard uncertainties of every considered source.

Regarding the digital signal processing (DSP), we have to take into account the bias of the processing algorithms and the uncertainties related with the rounding phenomena. The algorithm bias is caused by the finite implementation of the measurement algorithms and represents the deviation of the actual measured result with respect to the theoretical response, which the instrument should give. The rounding phenomenon is caused by the microprocessor finite wordlength. It can occur in every multiplication carried out in a fixed-point representation and in every addition and multiplication carried out in a floating-point representation. The related uncertainties can be modeled as follows [10], [11]:

$$u_{fixed} = \sqrt{\frac{2^{-2\cdot B_x}}{12}} \tag{2}$$

for each multiplication carried out by a fixed-point processor.

$$u_{floating,\, multipl} = \sqrt{0.18 \cdot 2^{-2\cdot B_m}} \tag{3}$$

$$u_{floating,\, add} = \sqrt{p \cdot 0.18 \cdot 2^{-2\cdot B_m}} \tag{4}$$

for each multiplication and addition, respectively, carried out by a floating-point processor. Here, $B_x$ is the fixed wordlength, $B_m$ is the number of bits used to represent the mantissa, and $p$ is a factor depending on the probability of rounding occurrence in an addition.

Regarding the software for the data acquisition board control and for the user interface, we can say that it does not contribute to the measurement result uncertainty, but obviously it is essential for the correct operation of the VI.

## III. Estimation of Combined Uncertainties

The VI measurement result is a function of many acquired samples, and this function is described by the measurement DSP algorithm. So, to evaluate the measurement result uncertainty, we have to know how the uncertainties of each acquired sample propagate through the DSP block.

Besides the experimental method, which consists of carrying out a statistically sufficient number of measurements with a statistically sufficient number of already realized instruments, we can use two other methods: a theoretical method, applying the "uncertainty propagation law" of the GUM, and a numerical method, simulating the physical process of the A/D conversion.

### A. Theoretical Method

It is possible to use a theoretical method applying the uncertainty propagation law of the GUM to the VIs. When a measurand estimate $y$ is determined from $N$ other samples $x_1, x_2, \ldots, x_N$, through a functional relation $y = f(x_1, x_2, \ldots, x_N)$, the combined standard uncertainty estimate $u_c(y)$ of the measurement result is the positive square root of the estimated variance $u_c^2(y)$, obtained from

$$u_c^2(y) = \sum_{i=1}^{N} \left(\frac{\partial f}{\partial x_i}\right)^2 u^2(x_i) + 2\sum_{i=1}^{N-1} \sum_{j=1,\, j\neq i}^{N} \frac{\partial f}{\partial x_i}\frac{\partial f}{\partial x_j} \cdot r(x_i, x_j) u(x_i) u(x_j) \tag{5}$$

where $u(x_i)$ is the estimated standard uncertainty associated with the sample estimate $x_i$ and $r(x_i, x_j)$ is the estimated correlation coefficient associated with the samples $x_i$ and $x_j$.

The evaluation of the correlation coefficients is often a very hard task, because they are also strictly dependent on the input signal. On the other hand, to ignore the correlations could cause a large underestimate of the uncertainties. So, the theoretical approach seems to be inapplicable because of the difficulties in the exact identification of correlation coefficients. But, if we consider separately each uncertainty source, we can observe that for the offset and its temperature drift, the gain and its temperature drift, and the long-term stability, the correlation coefficients are approximately equal to 1. Regarding the other uncertainty sources, the correlation coefficients can be supposed equal to 0. Moreover, in the case of errors due to gain, the relative standard uncertainty $u_r(x) = u(x)/|x|$ has to be considered constant on each input sample. In all other cases the absolute standard uncertainty $u$ has to be considered constant on each input sample.

Therefore, all of the uncertainty sources can be divided approximately into three classes:

1. completely correlated input quantities and $u_I = const$;
2. completely correlated input quantities and $u_{rII} = const$ ($u_r =$ relative uncertainty);
3. not correlated input quantities and $u_{III} = const$.

The same uncertainty source can belong to different classes; for example, the thermal drift offset belongs to the first class for an rms value measurement of a signal, but it belongs to the third class for the daily mean temperature calculated from 24 samples measured at each hour.

In this way, it is possible to overcome the difficulties of the exact evaluation of the correlation coefficients, since by means of the proposed classification, we can divide the error sources into three classes with supposed correlation coefficients exactly equal to 1 or 0. Furthermore, the uncertainty propagation law becomes easier to apply, that is respectively for the three classes:

$$u_{cI}(y) = u_I \sum_{i=1}^{N} \left(\frac{\partial f}{\partial x_i}\right) \tag{6}$$

$$u_{cII}(y) = u_{rII} \sum_{i=1}^{N} \left(\frac{\partial f}{\partial x_i} x_i\right) \tag{7}$$

$$u_{cIII}(y) = u_{III} \sqrt{\sum_{i=1}^{N} \left(\frac{\partial f}{\partial x_i}\right)^2}. \tag{8}$$

Starting from the above considerations, the idea of an approximate theoretical method has arisen. It consists of the following steps:

- to subdivide the uncertainty sources into the three classes;
- to carry out the root sum square of the uncertainties of each class, obtaining three values of uncertainty for each acquired sample;
- to apply the propagation law separately for each source class, getting three standard uncertainty values $u_{cI}$, $u_{cII}$, $u_{cIII}$;
- to carry out the root sum square of these three values obtaining the combined standard uncertainty of the measurement result.

There are some approximations in this method: the first one is implicit in the propagation law which is based on a first-order Taylor series approximation of $y$; the second one consists of combining the uncertainties after they are propagated, whereas, actually, the uncertainties first are combined in each acquired sample and then propagated through the software block; the last approximation is the subdivision of the uncertainty sources into the three classes with supposed correlation coefficient exactly equal to 1 or 0.

### *B. Numerical Method and Software Tool*

In some cases, the function describing the measurement algorithm is not an analytical and derivable function, so the proposed theoretical procedure is not applicable. To avoid this obstacle, we developed a software tool that simulates the A/D conversion process and the introduction of the sources of errors. By means of this tool, it is possible to evaluate the combined standard uncertainties associated with the measurement results, using a Monte Carlo approach.

The numerical method can be applied if the DSP block is already designed and realized. In the first stage, the input signal is digitally simulated and sent to the DSP block. By simulating a statistically sufficient number of measures, and by evaluating the mean and standard deviation of the results, we can estimate the standard uncertainty generated in the software block.

The algorithm bias (if the input signal is always the same) is an error with standard deviation equal to 0; therefore, the difference between the obtained mean and the theoretical response that the instrument should give is exactly the bias. The estimate of the bias is often a very hard task, since it depends on the input signals as well as the algorithms. The search of the worst case could be useful to find an upper limit to the uncertainty. In many cases, the lack of knowledge of the bias becomes the main uncertainty source. The measured standard deviation is the uncertainty due to the rounding occurrences. Since the number of bits used to represent the numbers is usually very high, this uncertainty is often negligible in comparison with the other ones.

Subsequently, an uncertainties simulation block is inserted between the input signals simulation block and the DSP block, simulating a set of measurements carried out by different realizations of the same instrument. The uncertainty simulation block takes into account all the uncertainty sources. To simulate the pre-gain and post-gain offset and their temperature drift, four constant values are added to each sample of the signal. Each one of these values is a random number within the range declared by the manufacturer. For each simulated measurement, the generated random numbers change so that they lie in the specification range according to the chosen distribution. It is possible to choose among rectangular, normal and triangular distribution. In the same way, gain and its temperature drift, the long-term stability, and temperature drift of the onboard calibration reference are simulated. In this case, each sample of the signal is multiplied by four constant values. The INL is simulated by distorting the transfer function with components of second, third, fourth, and fifth order, so that the maximum deviation from a linear transfer function is always smaller than the maximum INL value declared in the specification. A white noise is added to simulate the thermal noise; to simulate the crosstalk interference, another signal is added. The time jitter errors are simulated by multiplying a random number, within the range $\pm\tau_\alpha$, by the derivative of the signal; then, the so-obtained values are added to each sample. Regarding the settling time errors, the software tool calculates the range of accuracy for the actual settling time; a random number within this range is generated and multiplied by the actual step between the considered sample and the previous one; the so-obtained values are added to each sample. Last, after the simulation of the quantization process, random numbers equally distributed in the range ±DNL are added to each quantization level, simulating the DNL errors. After a statistically sufficient number of simulated measurements, we can calculate the standard deviation that is the combined standard uncertainty of the measurement result.

The main advantage of this method is that it intrinsically takes into account every possible correlation between each quantity. Moreover, by using this method it is possible to easily separate the uncertainties related with the DSP block from the ones generated in the A/D conversion process.

## IV. VALIDATION OF THE PROPOSED APPROACHES

It is obvious that we have to validate the effectiveness of the described approaches, before considering them as reliable. In fact, the theoretical method is based on a series of approximations of which we have to prove the plausibility; the numerical approach is strictly dependent on how the A/D conversion process and the introduction of the errors are simulated.

Therefore, with the aim of verifying the proposed methods, we applied both of them on various DSP basic blocks, which are typical of a measurement chain, and compared the obtained results with the ones obtained from experimental tests. For example, in the following, the procedure for the mean of 2000 samples, the RMS of 2000 samples, and a finite impulse response (FIR) filter with 11 coefficients is reported. The VI is composed of a Krohn–Hite™ VIII order Butterworth lowpass filter, the National Instruments AT-MIO-16E10 data acquisition board (DAQ) (16 single-ended or eight differential channels, successive approximation 12-bit Adc, 100 kS/s max sampling rate, ±10 V maximum input signal range), and a PC with an INTEL™ 200 MHz processor. The LabView™ 5.1 is the programming language used to drive the acquisition board, to process the acquired samples, and to realize the user interface. The utilized sampling rate is 10 kS/s. The example test signal

TABLE I
UNCERTAINTY SOURCES

| Uncertainty source | Manufacturer specification | Class | Standard uncertainty values |
|---|---|---|---|
| pre-gain offset | ± 2 μV | I | 1.2 μV |
| post-gain offset | ± 1000 μV | I | 577 μV |
| pre-gain offset temperature coefficient | ± 15 μV/°C | I | 8.7 μV |
| post-gain offset temperature coefficient | ± 480 μV/°C | I | 277 μV |
| gain | 0.05 % | II | 289 ppm |
| gain temperature coefficient | ± 20 ppm/°C | II | 12 ppm |
| temperature coefficients of the onboard calibration reference | ± 5 ppm/°C | II | 2.9 ppm |
| long-term stability of the onboard calibration reference | ± 15 ppm/√(1000 h) | II | 25 ppm |
| INL | ± 1 LSB | III | 2819 μV |
| DNL | ± 0.5 LSB | III | 1410 μV |
| quantization | ± 0.5 LSB | III | 1410 μV |
| noise | 0.07 LSB rms | III | 342 μV |
| settling time for full-scale step | ± 0.1 LSB in 100 μs | III | 282 μV |
| time jitter | ± 5 ps | III | 140 μV |
| cross talk | - 80 dB | III | 707 μV |

is a 2-kHz sinusoid with a 9-V peak value and is generated, for the experimental tests, by the National Instruments™ PCI-MIO-16XE10 board with a 16-bit D/A converter. The sampling is coherent with the generated sinusoid, so in this way, the bias of the three algorithms is equal to 0. We consider a Type B evaluation of standard uncertainties, based on the manufacturer's specifications, assume rectangular distributions, and suppose operation within $\pm 1$ K of the DAQ self-calibration temperature, within $\pm 10$ K of factory calibration temperature, after one year of the factory calibration, and setting the gain equal to 0.5.

In Table I, the considered uncertainty sources, the manufacturer specification, and the standard uncertainty values (evaluated as in Section II) are reported.

Because the number of bits used to represent the mantissa is equal to 52, the uncertainties introduced by microprocessor finite wordlength are negligible compared with the other ones.

To apply the proposed theoretical method we have to carry out, as the first step, the root sum square of the uncertainties of each class, obtaining the three values of uncertainty for each acquired sample

$$u_I = 640\ \mu\text{V} \qquad u_{rII} = 290\ \text{ppm} \qquad u_{III} = 3555\ \mu\text{V}.$$

The second step consists of applying the uncertainty propagation law.

Let us consider the mean of $N$ samples. In this case

$$y = \frac{\sum_{i=1}^{N} x_i}{N} \tag{9}$$

and

$$\frac{\partial f}{\partial x_i} = \frac{1}{N} \tag{10}$$

so, (6)–(8) become, respectively

$$u_{cI}(y) = u_I \tag{11}$$

$$u_{cII}(y) = u_{rII}\frac{\sum_{i=1}^{N} x_i}{N} \Rightarrow u_{r_{cII}}(y) = u_{rII}(x) \tag{12}$$

$$u_{cIII}(y) = \frac{u_{III}}{\sqrt{N}}. \tag{13}$$

For the RMS value of $N$ samples

$$y = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}} \tag{14}$$

$$\frac{\partial f}{\partial x_i} = \frac{x_i}{N\sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}}} \tag{15}$$

so, (6)–(8) become, respectively

$$u_{cI}(y) = u_I \frac{\sum_{i=1}^{N} x_i}{N}\sqrt{\frac{N}{\sum_{i=1}^{N} x_i^2}} \tag{16}$$

$$u_{cII}(y) = u_{rII}\sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}} \Rightarrow u_{r_{cII}}(y) = u_{rII}(x) \tag{17}$$

$$u_{cIII}(y) = \frac{u_{III}}{\sqrt{N}}. \tag{18}$$

Regarding a finite impulse response filter

$$y = \sum_{i=1}^{N} a_i x_i \tag{19}$$

and

$$\frac{\partial f}{\partial x_i} = a_i \tag{20}$$

where $a_i$ are the coefficients of the filter.

In this case, (6)–(8) become, respectively

$$u_{cI}(y) = u_I \sum_{i=1}^{N} a_i \tag{21}$$

$$u_{cII}(y) = u_{rII}\sum_{i=1}^{N} a_i x_i \Rightarrow u_{r_{cII}}(y) = u_{rII}(x) \tag{22}$$

$$u_{cIII}(y) = u_{III}\sqrt{\sum_{i=1}^{N} a_i^2}. \tag{23}$$

Last, carrying out the root sum square of $u_{cI}$, $u_{cII}$, and $u_{cIII}$, we get the combined standard uncertainty of the measurement result.

In Table II, the so-obtained values of the combined uncertainty are reported. The measurands are respectively the mean, the RMS value and the filtered sinusoid peak value.

TABLE II
COMBINED STANDARD UNCERTAINTY

| Algorithm | Theoretical uncertainty | Numerical uncertainty | Experimental uncertainty |
|---|---|---|---|
| Mean | 645 μV | 647 μV | 512 μV |
| RMS | 1847 μV | 1859 μV | 1532 μV |
| FIR filter | 2895 μV | 3001 μV | 2365 μV |

These results are compared with the ones obtained by applying the numerical methods and carrying out 10 000 simulated measurements. The numerically-obtained results are slightly higher than the ones obtained by using the approximated theoretical method. It is probably caused by not taking into account some correlation of the input sample uncertainties with the theoretical method (as an example, the quantization errors for dc signals). But, the differences are smaller than 1%, so although the theoretical approach leads to a small uncertainty underestimate, the approximations of this method are fully justifiable.

In Table II, we also report the results of the experimental tests, obtained also in this case, from a set of 10 000 measurements. The experimentally obtained uncertainties are (as prescribed in the GUM) the root sum square of the uncertainty actually measured and of the uncertainties due to offset, gain, temperature drift, and nonlinearity because the last quantities, having a systematic behavior, cannot be pointed out as uncertainty in a single DAQ test.

The experimental results are lower than the theoretically obtained ones, also without considering the uncertainties introduced in the signal generation process and in anti-alias filtering. Therefore, these results validate the considered model and the values of the various uncertainty sources of the utilized data acquisition board.

We carried out other experimental tests on other DSP blocks, using various signals and other acquisition boards, and also in these cases, the results validate the proposed procedures.

## V. CONCLUSION

In this paper, two methods to estimate the measurement uncertainty of a virtual instrument have been proposed. The main advantage of both methods is that it is not necessary to calculate the correlation coefficients as prescribed in the GUM.

The numerical method is easy to apply, and it is possible to separate the uncertainties related with the DSP block from the ones generated in the A/D conversion process; but it is necessary that the DSP block is already designed and realized.

On the contrary, the approximated theoretical approach, if applicable, can be helpful also in the phase of instrument design, when the DSP block, implementing the measurement algorithm, is not realized yet. Moreover, the approximated theoretical method can be useful to implement in the virtual instruments, algorithms that furnish, besides the measurement result, the associated standard uncertainty.

The results obtained by using the two methods have been compared and are practically coincident. They are in good agreement also with the experimental tests, validating the proposed approaches and the values of the various uncertainty sources of the utilized data acquisition boards.

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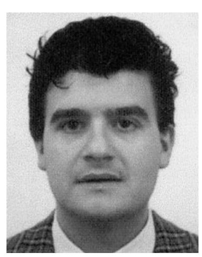

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