INTERNATIONAL JOURNAL of SMART GRID
C. Spataro, Vol.7, No.4, December, 2023

Characterisation of Measurements for Smart Grids

Ciro Spataro

Department of Engineering, University of Palermo, Viale delle Scienze ed.9 90128, Palermo Italy

(ciro.spataro@unipa.it)

Received: 13.11.2023 Accepted:15.12.2023

Abstract- The management of smart grids requires advanced and complex measuring systems because of the continuous development of electricity production, transmission, and distribution systems. These measurement systems, because of their complexity, are only based on analog-to-digital conversion. To characterise the quality of such measurements, it is necessary to evaluate their measurement uncertainty. With this aim, this paper presents an approach based on the Monte Carlo method. By using a specially designed simulator and inputting the characteristics of the employed transducers and analog-to-digital converters, the method allows not only estimating uncertainties but also getting the probability density functions associated with measurements. The proposed method can easily estimate the impact of different sources of error on the measurement uncertainty, allowing for the proper design of the measurement system and the proper choice of transducers and analog-to-digital converters.

Keywords: Smart grids; power quality; Monte Carlo methods; analog-to-digital conversion; uncertainty evaluation.

1. Introduction

The urgent need to transition to clean energy has led to an increased use of renewable sources, such as solar and wind. However, due to the variability of these sources, managing production, transmission, distribution, and use of electricity has become more challenging [1-5].

To reduce the demand for new and high-priced infrastructure and maximise power grid efficiency, reliability, and stability, the use of digital technologies, smart sensors, software, and complex measurement systems is becoming more common, creating a "Smart Grid".

In this context, measurements are playing an increasingly important role [6-20]. It is essential to monitor continuously not only the usual quantities, such as voltage, current, active power, and reactive power, but also all the parameters related to power quality.

Because of the complexity of these measurements, they are performed exclusively by employing the analog-to-digital conversion (A/D) and the subsequent digital processing of the acquired data. Measuring instruments made with a data acquisition card (DAQ) connected to a personal computer offer a more economical and flexible alternative compared to standalone instruments that are usually dedicated to a defined measuring purpose. However, in both cases, it is necessary to use transducers with adequate bandwidth characteristics because of the high voltage and current values present in power grids.

As with any measuring process, to assess the quality of such measurements, it is necessary to evaluate their uncertainty following the rules prescribed in the "Guide to the Expression of Uncertainty in Measurement" [21]. For the measures covered by this paper, these rules can be summarised in the following four steps:

- identifying error sources that occur during signal transduction, A/D conversion, and digital processing of acquired data.
- estimating the uncertainty associated with each identified source.
- obtaining the uncertainty for each acquired sample by combining the uncertainties associated with each error source.
- investigating how uncertainties on each sample acquired propagate along the digital signal processing and affect the measurement result.

Particularly in the A/D conversion process, the initial step is the most challenging one. Manufacturers provide numerous parameters to characterise their A/D converters or DAQ [22]. Furthermore, these parameters are frequently defined and measured in a variety of ways. The presence of various standards regarding the characterisation of the A/D converters is one of the factors that led to this situation [23-24]. Therefore, one of the purposes of this work is to identify a minimum set of parameters that can fully characterise the measurement chain.

The second step can be carried out by statistical methods (Type A evaluation according to [21]) or by using manufacturers' specifications (Type B assessment). The second approach does not require any type of testing and is thus faster and less expensive. It should be noted that, even though thirty years have passed since the first publication of [21], many manufacturers still do not disclose uncertainty values, but only the maximum permissible error. Therefore, subjective assumptions about the probability density functions are necessary to assess the uncertainties associated with every single error source. This work will analyse both methods, highlighting their respective advantages and disadvantages.

The proposed methodology for performing the last two steps simultaneously is the use of the Monte Carlo method [25], which involves creating a software tool that simulates the introduction of error sources generated by all the components of the measurement system.

The paper is organized as follows: Chapter II presents the proposed methodology for estimating measurement uncertainty, describing in detail how the four above steps are performed. In Chapter III, the suggested approach is validated by experimental testing. Chapter IV describes some applications to typical measurements on smart grids and explains how the Monte Carlo method can be easily utilized to assess the impact of each source of error on the measurement result. Some final remarks and conclusions are depicted in Chapter V.

2. Uncertainty Evaluation

The measurement devices used in smart grids typically include voltage probes (such as differential, active, low capacitance, and passive types) and current probes (such as Hall effect sensors, current clamps, shunts, and Rogowski coils). These transducers can be affected by several sources of errors, including offset, gain, nonlinearity, hysteresis, spurious tones, settling time, and thermal noise.

The situation is much more complicated for the A/D conversion process. At least the following sources must be considered [23-24]: settling time, thermal noise, crosstalk, timing jitter, quantization, differential nonlinearity, spurious tones, offset, gain, and integral nonlinearity.

Another source to consider would be the non-linearity of the frequency response of transducers and A/D converters. However, since typical signals in smart grids have a very limited frequency band compared to the usual employed measurement system dynamic range, these errors can be overlooked.

Considering all the sources of error can be a challenging and time-consuming task, especially since manufacturers rarely disclose all the relevant parameters. To address this issue, the methodology described in [26] can be used to analyse the impact of each error source on the acquisition of a single sinusoid in the frequency domain. This analysis reveals that:

- offset errors appear as a DC component on the spectrum.
- gain errors cause a variation in the width of the spectral line corresponding to the acquired sine wave.
- the non-linearities generate a harmonic distortion of the acquired signal.
- spurious tones (usually caused by electromagnetic interference) appear as the corresponding spectral lines.
- thermal noise, hysteresis, crosstalk, settling time, timing jitter, quantization, and differential nonlinearity generate a broadband noise, which can be approximately considered as being uniformly distributed throughout the acquired spectrum.

To investigate how errors propagate during digital processing, an additional classification is useful:

- offset errors and spurious tone errors are not dependent on the acquired signal and appear with the same intensity regardless of the characteristics of the acquired signal itself.
- gain and nonlinearity errors depend on the amplitude of the acquired signal.
- the broadband noise depends on the shape, amplitude, and frequency of the input signal. However, for the measurements covered by this work, this noise can be considered independent of the input signal with good approximation.

Based on the provided information, it can be concluded that the minimum set of parameters required for accurately evaluating uncertainties includes offset, gain, total harmonic distortion (THD), total spurious distortion (TSD), and signal-to-noise ratio (SNR). By considering the values of these parameters, it becomes possible to account for all the error sources and their unique features of propagation through the digital processing block of the measurement chain.

To combine the uncertainties associated with the five error sources in each acquired sample and to take into account the uncertainty propagation during digital signal processing, an "ad hoc" simulator was developed using LabView software.

This simulator is placed between an input signal simulator and the software block that executes the measurement algorithm. The input signal simulator generates *n* samples as if they were obtained from an ideal measurement system. These samples are sent to the error simulation block and then to the measurement algorithm block. The simulation is performed *m* times using a FOR loop, generating *m* different measurement results as if they were obtained from *m* different realizations of the same measurement chain.

The simulation of the errors represented by the selected parameters is carried out as follows:

- offset errors - at each trial, a constant value is added to the *n* input samples. This value is randomly extracted from the offset range provided by the manufacturer's specifications and is consistent with a rectangular distribution.
- gain errors - at each trial, the *n* input samples are multiplied by a constant value. This value is randomly extracted from the gain range provided by the manufacturer's specifications and is consistent with a rectangular distribution.
- THD errors - the transfer function is distorted by harmonic components that range from the second to the tenth order. These components' amplitudes vary randomly with each iteration but always generate a total harmonic distortion (THD) value that matches the manufacturer's specifications.
- TSD errors - to simulate spurious tones, two sinusoidal signals are added. The amplitude and phase shift of

these sinusoids vary randomly at each iteration but they always generate a TSD value that matches the manufacturer's specifications.

- SNR errors – at each trial, Gaussian noise is added to the input signal to produce a THD value that matches that specified by the manufacturer.

The *m* measurement results are collected outside the FOR loop. Then, the main value, the standard deviation, which represents the starting uncertainty, and the probability density function (PDF) are calculated.

Fig. 1 shows a simplified flow diagram of the simulator.

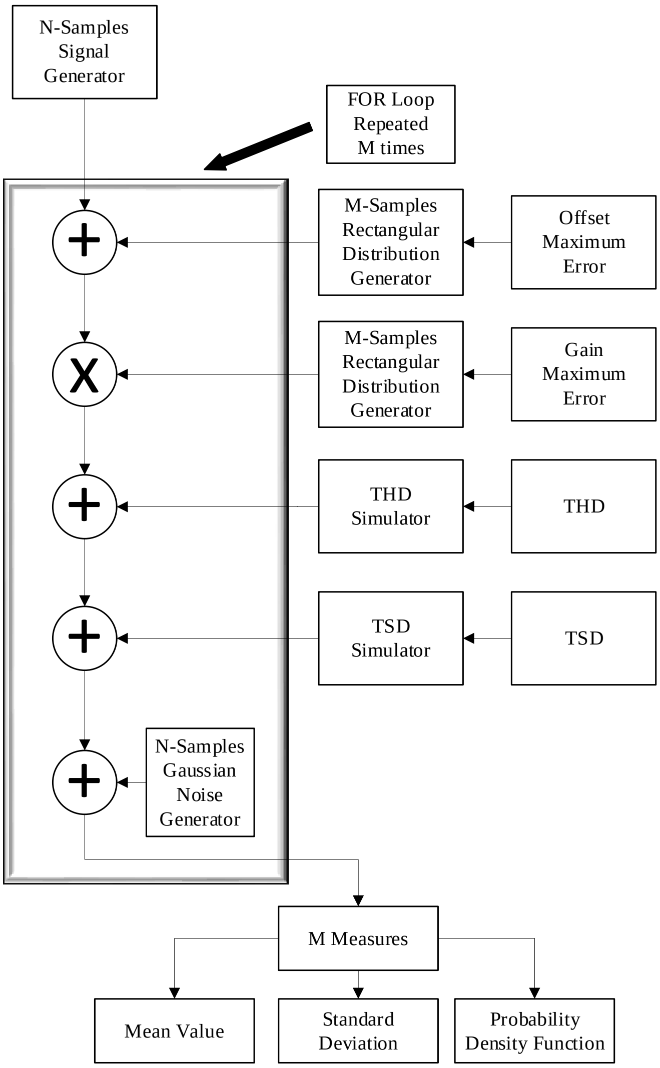

Fig. 1. Flow diagram of the simulator

3. Validation

To validate the effectiveness of the proposed approach, it was applied to actual measurements and compared with the results obtained from experimental tests.

Two models of DAQs were utilized in the tests, namely the National Instrument™ (NI) USB 9239 and the NI USB 9225, both equipped with 24-bit sigma-delta converters. The performed measurement was the root mean square (RMS) value of a 60 Hz sine wave signal generated by the Fluke™ 5720A multifunction calibrator, which can be used as a reference standard. The signal was acquired at a sampling rate of 2 kS/s, with 200 samples taken in each acquisition. For each test, 20 measurements were carried out on different days while maintaining the laboratory temperature in the range of 17-23 °C. To obtain the uncertainty values, the proposed approach was applied by carrying out 1000000 trials. The LabView language was used to drive the data acquisition boards and extract the RMS values from the acquired samples.

All the uncertainty values reported are expressed as expanded uncertainties with a 95 % confidence level.

The first experiment was performed by acquiring a 5 V RMS sinusoidal signal by using the NI USB 9239 DAQ. Table 1 reports, for this board and this measurement, the values of the five parameters for the uncertainty evaluation.

Table 1. Specifications for the NI USB 9239 DAQ

Parameter	Value
offset	± 6 mV
gain	± 0,13 %
THD	99 dB
TSD	128 dB
SNR	100 dB

Starting from these values and applying the proposed approach, an uncertainty of 6 mV was estimated. For this specific measurement, the Fluke 5720A, used in AV mode and within the range of 22 V, has an expanded uncertainty of 230 μV.

Fig. 2 shows the 20 measured values; the dashed lines represent the uncertainty interval estimated by using the proposed approach and the continuous lines represent the uncertainty interval of the Fluke calibrator.

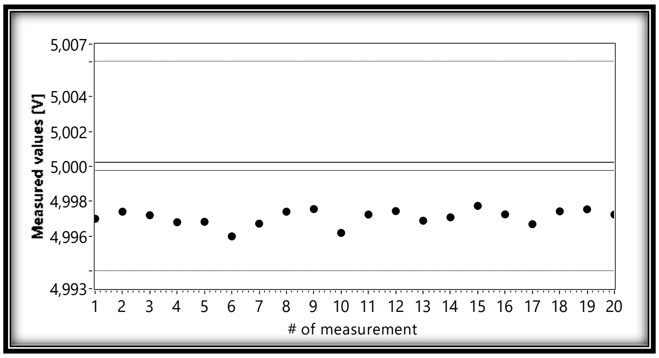

Fig. 2. Voltage RMS values measured by using the NI USB 9239 DAQ

All the measured values fall within the calculated uncertainty range, thereby confirming the obtained uncertainty estimate. Although the actual standard deviation of the 20 measured values is significantly smaller than the estimated standard uncertainty, it is important to note that this apparent overestimation is because certain uncertainty sources such as offset, gain, and INL cannot be fully highlighted in a test carried out with a single DAQ.

In the second experiment, the NI USB 9225 DAQ was utilised to acquire a 200 V RMS sinusoidal signal. Table 2 presents the values of the five parameters employed in the uncertainty evaluation for this board and measurement.

Table 2. Specifications for the NI USB 9225 DAQ

Parameter	Value
offset	± 22 mV
gain	± 0,23 %
THD	95 dB
TSD	128 dB
SNR	103 dB

Starting from these values and applying the proposed approach, an uncertainty value of 300 mV was assessed. For this measurement, the expanded uncertainty of the Fluke 5720A, used in AV mode and the range 220 V is 10 mV. Fig. 3 displays the 20 measured values, along with the estimated uncertainty interval (dashed lines) and the calibrator uncertainty interval (continuous line).

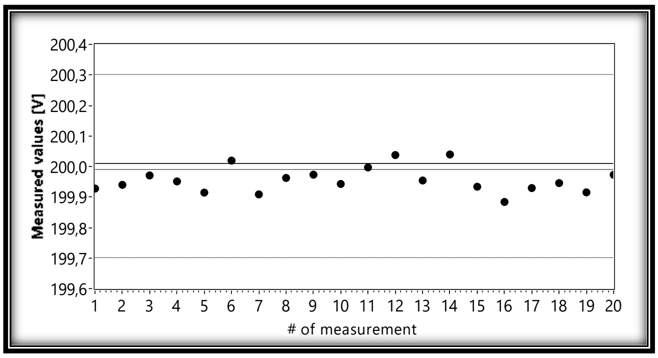

Fig. 3. Voltage RMS values measured by using the NI USB 9225 DAQ

Again, the 20 measures fall within the uncertainty range assessed by the Monte Carlo approach.

To provide an example of a more complex measurement chain, the proposed approach was applied to the RMS value measurement of a 60 Hz 10 A RMS sinusoidal current, generated by the Fluke 5727A amplifier driven by the Fluke 5720A calibrator.

The signal was transduced through a current shunt PR electronics 7005 with the following characteristics: 0,1 Ω nominal value; 1% tolerance; 20 W maximum power. The transduced signal was acquired by the NI USB 9239 DAQ whose characteristics are indicated above.

Starting from these values and applying the proposed approach, an uncertainty value of 120 mA was estimated. For this measurement, the expanded uncertainty of the Fluke 5720A plus the Fluke 5727A, used in AC mode and in the range 11 A is 10 mA. In Fig. 4, the 20 measured values, the estimated uncertainty interval, and the uncertainty interval of the current generation system are reported.

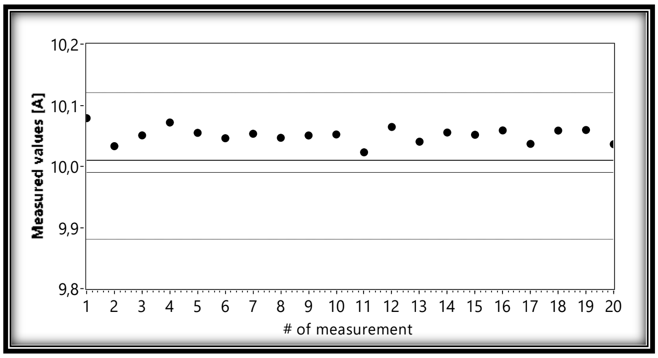

Fig. 4. Current RMS values measured by using the 0,1 Ω shunt and the NI USB 9239 DAQ

Once again, the measured values are within the estimated uncertainty range, giving further confirmation of the validity of the proposed approach.

Manufacturers of transducers and DAQs do not always provide all the necessary parameters required to apply the proposed approach. In these cases, where a statistically sufficient number of all measurement system components are available, a type A uncertainty evaluation can be performed.

As an example, let us consider the low-cost 12-bit DAQ NI USB 6008. For this board, the manufacturer only provides absolute accuracy at full scale. However, by having ten DAQs of this model, it was possible to perform a statistical evaluation of the uncertainties associated with the proposed five parameters.

For each DAQ, using a Fluke 8508A multimeter in DV mode as a reference, offset and gain were measured by drawing the transfer characteristics obtained via a five-point least minimum squares method.

Acquiring a full-scale sinewave generated by the Fluke 5720A calibrator in DV mode, THD, TSD and SNR values were measured for each DAQ using an FFT test.

Table 3 shows the values obtained from tests for an input range of ± 10 V.

Table 3. Specifications for the NI USB 9008 DAQ

Parameter	Value
offset	± 1,8 mV
gain	± 0,12 %
THD	63 dB
TSD	70 dB
SNR	68 dB

Using these values and applying the proposed approach, an uncertainty value of 6,4 mV was estimated.

To verify the accuracy of the assessment of the five parameters, 60 measurements of the RMS value were conducted on different days. This was achieved by employing three randomly selected DAQs from the pool of ten available boards. A sinusoidal test signal with an RMS amplitude of 5 V was generated by the Fluke 5720A.

In Fig. 5, the estimated uncertainty interval, the calibrator uncertainty interval, and the 60 measurement results are reported (values 1-20 obtained by using the DAQ N.1; values 21-40 obtained by using the DAQ N.2; values 41-60 obtained by using the DAQ N.3).

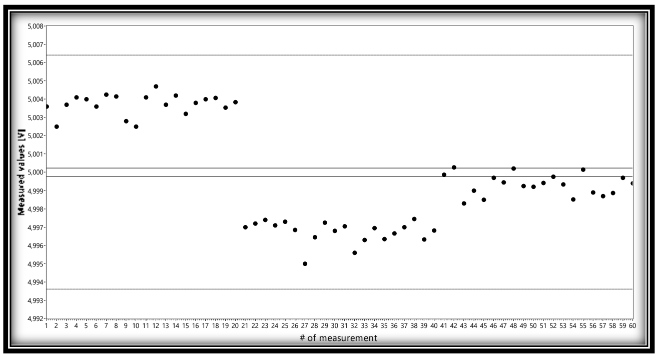

Fig. 5. Voltage RMS values measured by using three NI USB 9008 DAQ

The measurement results, once again, comply with the estimated uncertainty range, thus certifying the validity of both the proposed approach and the estimate of the five parameters.

By conducting a Type A evaluation, it is possible to consider electromagnetic disturbances, which have the potential to induce spurious tones, modify the offset value, and/or elevate the noise floor, as evidenced in [27].

Electromagnetic disturbances are caused by couplings with the measuring system's connection cables. Therefore, the actual values of offset, TSD and SNR should be assessed for the acquisition channel, including cables. This task can be easily achieved using the procedure described in [27].

For instance, another test was performed in proximity to a power drive system for a three-phase synchronous motor widely described in [28].

The test signal is a 200 V RMS sinusoid acquired by the NI USB 9225 DAQ. This power system produces a heavy inductive interference with the measurement system. Proceeding as indicated in [27], this interference was quantified. It causes both spurious tones and broadband noise, reducing the TSD value from 128 dB to 73 dB and the SNR value from 103 dB to 62 dB.

Using the new TSD and SNR values and applying the proposed approach, an uncertainty value of 1,3 V was estimated. Again, the chosen measurement was the RMS value of a 200 V RMS sinusoidal signal generated by the Fluke calibrator.

Performing 20 measurements near the power drive system, the values reported in Fig. 6 were obtained. These measurement results, again, lie within the estimated uncertainty range.

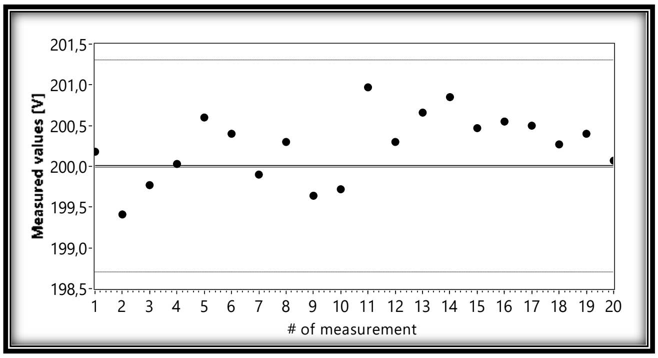

Fig. 6. Voltage RMS values measured by using the NI USB 9225 DAQ in proximity to a power drive system

4. Proposed Method Application

The Monte Carlo method allows obtaining, in addition to the standard deviations (which according to [21] represent the measurement uncertainties), also the mean values and the probability density functions (PDF). By analysing the PDF, it is possible to determine if measurement errors cause a bias in the measurement result and to identify potential asymmetries in the distributions. Thus, it is possible to estimate confidence intervals related to uncertainty with greater accuracy.

The proposed method has another advantage, as it can easily estimate the impact of various sources of error on the measurement uncertainty. This final point enables the precise design of the measurement system and the right choice of transducers, A/D converters, and DAQ.

To give an example, let us consider acquiring a voltage signal through a low-cost acquisition channel that includes a voltage probe and a data acquisition system (DAQ), with the characteristics listed in Table 4.

Table 4. Typical specifications for a low-cost acquisition channel

Parameter	Value
offset	± 1,2 mV
gain	± 1,3 %
THD	70 dB
TSD	70 dB
SNR	60 dB

Let us consider the measure of the DC value, RMS value, FFT fundamental frequency amplitude, and harmonic distortion. The characteristics of the acquired voltage signal are listed in Table 5.

Table 5. Components of the simulated voltage signal

Peak value [V]	2	200	20	10
Frequency [Hz]	0	50	150	250

For every one of the four measures mentioned above, the proposed approach was applied to this signal by running 1000000 iterations.

To get the total uncertainty associated with measurements, it is necessary to simulate the effects of all error sources simultaneously.

To assess the impact of a specific source on the uncertainty, it is sufficient to apply the Monte Carlo method by simulating only its effect.

Table 6 reports, for each measurement, the expected values, the estimated bias, and standard uncertainties obtained by considering all the error sources at once and by considering the error sources individually.

Table 6. Expected values, estimated bias, and standard uncertainties

Measure	DC value [V]	RMS value [V]	FFT 50 Hz [V]	Harmonic distortion [%]
Expected value	2,000	142,310	141,421	11,180
Bias All error sources	0	0,013	0	0,030
Uncertainty All error sources	1,0	1,2	1,2	0,10
Uncertainty Offset errors	0,70	0,010	0	0
Uncertainty Gain errors	0,015	1,1	1,1	0
Uncertainty THD error	0	0,030	0,020	0,003
Uncertainty TSD error	0	0,50	0,40	0,008
Uncertainty SNR error	0,10	0,10	0,10	0,09

From these values, it is possible to make various considerations. For example, the offset is virtually the only error that affects the measurement of the DC value. In contrast, offset and gain errors have no impact on the harmonic distortion measurement.

Other useful information can be obtained by analysing the PDF generated by the Monte Carlo approach. For instance, Fig. 7 reports the estimated PDF generated by 1000000 trials of harmonic distortion measurements.

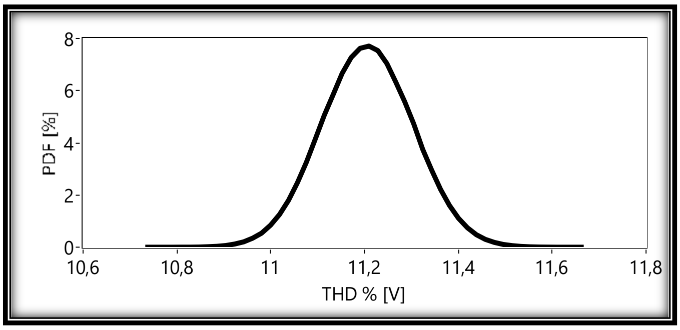

Fig. 7. PDF of harmonic distortion measurement

In this case, the distribution shape is Gaussian and, therefore, a 95 % confidence level can be correctly evaluated multiplying the standard uncertainty by a coverage factor k = 1,96.

Fig. 8 reports the estimated PDF generated by 1000000 trials of DC value measurements.

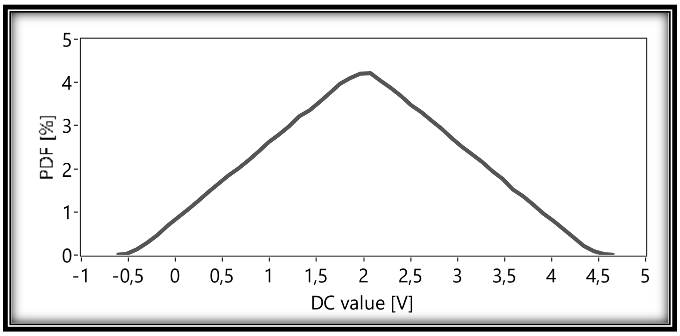

Fig. 8. PDF of DC value measurement

Here, due to the triangular shape of the distribution, it is not appropriate to use a Gaussian distribution to determine the correct confidence interval. The coverage factor for a triangular distribution is equivalent to 2,44 for a 95 % confidence level, so assuming a Gaussian distribution would result in a 20 % uncertainty underestimate.

5. Conclusion

In this paper, the problem of uncertainty estimation for measurements in smart grids is explored. A Monte Carlo approach was used to obtain the values of the combined expanded uncertainty of measurement results, considering the various error sources introduced during signal conditioning and A/D conversion, as prescribed in [21].

Simulation analysis showed that the parameters of offset, gain, THD, TSD, and SNR take into account all the uncertainties that arise during the measurement process and their specific behaviour during digital signal processing. Based on the values of these parameters, it is possible to evaluate the uncertainty values.

To demonstrate this assertion, the method was applied in real measurements and the results were compared to those obtained through experimental tests. The comparison showed that the suggested method leads to an accurate estimation of the uncertainties.

Unfortunately, the five parameters suggested here are not always included in the specifications and often are defined and measured in different ways. In these cases, manufacturers should be consistent in declaring, defining, and measuring the parameters that qualify their products. This could only be achieved with the full harmonization of all standards dealing with the characteristics of transducers, A/D converters, and DAQs.

An additional advantage of the proposed method is the ability to generate the actual probability density functions associated with the measurement, allowing for the calculation of accurate coverage levels and avoiding uncertainty underestimates in presence of not-Gaussian distributions.

Moreover, the Monte Carlo approach can easily estimate the effect of various sources of error on the measurement uncertainty. This allows for the accurate design of the measurement system and the selection of appropriate transducers and A/D converters.

Although the proposed simulator has been used for simulated signals, it can also be employed for acquired signals. Therefore, it can be implemented in the software part of the measurement system to estimate the uncertainty in real time taking into account the specificity of the acquired signal.

In the future, the study intends to analyse the measurements taken with two acquisition channels, such as power and energy measurements. In these cases, phase errors generated by both transducers and multi-channel A/D converters need to be considered.

References

[1] S. Sagiroglu, Y. Canbay, and I. Colak, "Solutions and Suggestions for Smart Grid Threats and Vulnerabilities" International Journal of Renewable Energy Research, vol.9, no.4, 2019.

[2] A. Nasiri, A. Bani-Ahmed, and I. Stamenkovic, "Foundational Support Systems of the Smart Grid: State of the Art and Future Trends", International Journal of Smart Grid, vol.2, no.1, 2018.

[3] D. Bishnoi, H. Chaturvedi, "A Review on Emerging Trends in Smart Grid Energy Management Systems", International Journal of Renewable Energy Research, vol.11, no.3, 2021.

[4] S. N. Saxena, "Smart Distribution Grid and How to Reach the Goal", International Journal of Smart Grid, vol.3, no.4, 2019.

[5] A. AlKassem, "The Integration of Intermittent Renewable Energy Sources to Smart Grid: A Comprehensive View", International Journal of Renewable Energy Research, vol.12, no.3, 2022.

[6] L. Peretto, "The role of measurements in the smart grid era", IEEE Instrumentation & Measurement Magazine, vol. 13, no. 3, pp. 22-25, 2010.

[7] B. Velkovski, M. Markovska, Z. Kokolanski, D. Taskovski, and V. Dimchev, "Evaluating the uncertainty of a virtual power quality disturbance generator and its use in power quality classifier evaluation", Acta IMEKO, Vol.12, no.3, 2023.

[8] D. L. Carní and F. Lamonaca, "Toward an Automatic Power Quality Measurement System: An Effective Classifier of Power Signal Alterations," IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-8, 2022.

[9] R. Deshpande, M. S. Raghvendraprasad, "Power quality analysis of electrical distribution systems with asynchronous generators", International Journal of Renewable Energy Research, vol.8, no.4, 2018.

[10] R. Deshpande, M. S. Raghvendraprasad, "Analysis of Power Quality variations in Distributed Generation Systems", International Journal of Renewable Energy Research, vol.9, no.1, 2019.

[11] J. -P. Kitzig, S. Schlaghecke, and G. Bumiller, "Power Quality Measurement System with PMU Functionality Based on Interpolated Sampling", IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 4, pp. 1014-1025, 2019.

[12] M. Kingsley-Amaehule, R. Uhunmwangho, N. Nwazor, and K. Okedu, "Smart Intelligent Monitoring and Maintenance Management of Photo-voltaic Systems", International Journal of Smart Grid, vol.6, no.4, 2022.

[13] M. Faifer, C. Laurano, R. Ottoboni, S. Toscani, and M. Zanoni, "Harmonic Distortion Compensation in Voltage Transformers for Improved Power Quality Measurements", IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 10, pp. 3823-3830, 2019.

[14] S. K. Jain, P. Jain, and S. N. Singh, "A Fast Harmonic Phasor Measurement Method for Smart Grid Applications", IEEE Transactions on Smart Grid, vol. 8, no. 1, pp. 493-502, 2017.

[15] S. Gangopadhyay and S. Das, "Fuzzy Theory Based Quality Assessment of Multivariate Electrical Measurements of Smart Grids", IEEE Access, vol. 9, pp. 97686-97704, 2021.

[16] D.Istrate, D. Amaripadath, E. Toutain, R. Roche, and F. Gao, "Traceable measurements of harmonic (2 to 150) kHz emissions in smart grids: Uncertainty calculation", Journal of Sensors and Sensor Systems, vol 9, no. 2, pp. 375–381, 2020.

[17] T. D. Atmaja, D. Andriani, and R. Darussalam, "Smart Grid communication applications: Measurement equipment and networks architecture for data and energy flow", Journal of Mechatronics, Electrical Power, and Vehicular Technology, vol. 10, no 2, 2019.

[18] V. J. Foba, A. T. Boum, and C. F. Mbey, "Optimal Reliability of a Smart Grid", International Journal of Smart Grid, vol.5, no.2, 2021.

[19] F. A. de O. Nascimento, "Hartley Transform Signal Compression and Fast Power Quality Measurements for Smart Grid Application", IEEE Transactions on Power Delivery, 2023.

[20] E.L.Sousa et al., "Development a Low-Cost Wireless Smart Meter with Power Quality Measurement for Smart Grid Applications", Sensors, vol. 23, no 16, 2023.

[21] BIPM, IEC, IFCC, ILAC, ISO, IUPAC, IUPAP, and OIML, Evaluation of measurement data - Guide to the expression of uncertainty in measurement, Joint Committee for Guides in Metrology, JCGM100,2008.

[22] S. Rapuano, "Preliminary Considerations on ADC Standard Harmonization", IEEE Transactions on Instrumentation and Measurement, vol. 57, no. 2, pp. 386-394, 2008.

[23] IEEE Standard 1241-2023, Standard for Terminology and Test Methods for Analog-to-Digital Converters.

[24] IEC Standard 62008-2005, Performance characteristics and calibration methods for digital data acquisition systems and relevant software.

[25] BIPM, IEC, IFCC, ILAC, ISO, IUPAC, IUPAP, and OIML, Evaluation of measurement data - Supplement 1 to the "Guide to the expression of uncertainty in measurement" - Propagation of distributions using a Monte Carlo method, Joint Committee for Guides in Metrology, JCGM 101, 2008.

[26] S. Nuccio and C. Spataro, "Assessment of virtual instruments measurement uncertainty", Computer Standards & Interfaces, vol. 23, no. 1, pp. 39-46, 2001.

[27] S. Nuccio, C. Spataro, and G. Tine, "Virtual Instruments: Uncertainty Evaluation in the Presence of Electromagnetic Interferences," IEEE International Workshop on Advanced Methods for Uncertainty Estimation in Measurement, Sardagna, Italy, 2007.

[28] M. Caruso, A.O. Di Tommaso, R. Miceli, C. Nevoloso, and C. Spataro, "Uncertainty evaluation in the differential measurements of power losses in a power drive system", Measurement, vol. 183, 2021.