2025 IMEKO Joint Conference
TC8 - TC11 - TC25
Torino, Italy, September 14-17, 2025

Conformity Assessment of Impedance Parameters Meters by MonteCalc Uncertainty Toolkit

Marija Cundeva – Blajer, Monika Nakova, Kiril Demerdziev

Ss. Cyril and Methodius University in Skopje, Faculty of Electrical Engineering and Information Technologies, str. "Rugjer Boshkovikj" No.18, Skopje, Republic of North Macedonia,
mcundeva@feit.ukim.edu.mk, monika_nakova@yahoo.com, kdemerdziev@feit.ukim.edu.mk

Abstract **–The development of a calibration procedure for impedance parameters meters in the Laboratory for Electrical Measurements at the Ss. Cyril and Methodius University in Skopje is presented. The procedure encompasses evaluation of the measurement uncertainty in calibration of meters for electrical inductance and capacitance by two approaches: the mainstream GUM methodology and the stochastic Monte Carlo technique. For the Monte Carlo evaluation, an original universal software MonteCalc Uncertainty Toolkit, is developed in LabVIEW™. The Toolkit is applied on real experimental data derived from the RLC meter laboratory calibration. The gained outcomes are verified against the uncertainty results from the GUM methodology and the evident discrepancies are discussed. The MonteCalc Uncertainty Toolkit also encompasses an algorithm for decision making in the process of conformity assessment against different predefined acceptance criteria compliant with the ILAC G8:09/2019, applied for evaluation of the RCL meter calibration conformity against its technical specifications.**

Keywords: calibration of impedance parameters meters, measurement uncertainty, GUM, Monte Carlo, LabVIEW™.

I. INTRODUCTION

In recent years, digitalization has gained momentum and is a phenomenon that encompasses all industries and sectors, and calibration laboratories are part of it, [1]-[4]. The digital transformation of a calibration laboratory can involve many activities such as: new instrumentation, advanced calculation methods, innovative ways of issuing calibration certificates, a new reporting principle, and the like. The level of digitalization that will be achieved depends on the working conditions, staff, and financial capabilities of the laboratory. Trying to keep up with the pace of the digitalization process and changes in the way of working, most of the calibration laboratories are trying to introduce new practices in their daily work but also to increase their scope of calibration capabilities, [5], [6]. Following this trend, after the purchase of new reference standards and the successful expansion of the scope of accreditation according to ISO/IEC 17025:2017, [7], the Laboratory for Electrical Measurements (LEM), at the Ss. Cyril and Methodius University in Skopje (UKIM), has improved its existing calibration capabilities and methods for calculating the measurement uncertainty budget, [8]. In software improvements, attempts in LEM were made for additional methods of uncertainty calculations, [10]-[14].

In this contribution, the development of a calibration procedure for impedance parameters meters in the LEM at UKIM is presented. The procedure encompasses evaluation of the measurement uncertainty in calibration of meters for electrical inductance and capacitance by two approaches: the mainstream GUM methodology and the stochastic Monte Carlo technique, [15], [16]. For the both methodologies, an original universal software MonteCalc Uncertainty Toolkit, is developed in LabVIEW™, [17]. The Toolkit will be applied on real experimental data derived from the RLC meter laboratory calibration. The gained Monte Carlo outcomes will be verified against the uncertainty results from the GUM methodology and the evident discrepancies will be discussed. The MonteCalc Uncertainty Toolkit also encompasses an algorithm for decision making in the process of conformity assessment against different predefined acceptance criteria compliant with the ILAC G8:09/2019, [18], applied for evaluation of the RCL meter calibration compliance against its technical specifications. The embedded decision-making rules are:

- binary rule,
- binary rule with guard band,
- non-binary rule with guard band and with measurement uncertainty taken into account.

The model for determining the measurement uncertainty budget according to the GUM and the Monte Carlo method developed in the LabVIEW programming language will be described. Finally, the obtained results will be compared and the advantages of introducing new methods for calculating the measurement uncertainty budget will be presented and discussed.

II. DIFFERENT APPROACHES FOR CALCULATION OF UNCERTAINTY IN CALIBRATION

Measurement uncertainty is a crucial quantitative indicator of the reliability of measurement results. Without it, comparing measurements to each other, to reference values, or to standards would be impossible, [19]. In today's globalized marketplace, a universal approach to estimating measurement uncertainty is essential for international comparability and mutual recognition in metrology. The JCGM 100:2008-GUM, [15] effectively achieves this harmonization by providing a comprehensive set of tools for various measurement situations. This document's method for estimating uncertainty relies on the law of propagation of uncertainty (LPU), which has been successfully used worldwide for diverse measurement processes for many years. However, the LPU is not always the most complete method for estimating uncertainties across all measurement systems. It involves certain approximations, such as linearizing the measurement model and approximating the resulting quantity's probability distribution with a Student's t-distribution based on calculated effective degrees of freedom. These approximations limit its ability to fully propagate the probability distributions of influencing factors. To address these limitations of the GUM, the Supplement 1 of the JCGM 101:2008-GUM, [16] introduced the use of the Monte Carlo method for propagating the full probability distributions. This allows for handling a wider range of measurement problems that the LPU alone could not cover. The GUM specifically guides the application of Monte Carlo simulations in metrology, recommending algorithms best suited for estimating uncertainties in this field. Different application cases of Monte Carlo simulations for evaluation of the uncertainties of testing and calibration have been published, [19], [20]. According to the already established LEM practices, the initial calculation of the measurement uncertainty budget in calibration procedures is in accordance to GUM. The influence of the measurement uncertainty components is mathematically described through type A and type B evaluation. The type A measurement uncertainty component u_A, with the sensitivity coefficient c_A is calculated through statistical analysis of predefined number of the measurements of the calibration artifact, while the type B measurement uncertainty component is calculated through the contribution of the calibrator accuracy u_{B1}, the calibrator resolution u_{B2}, the calibrator calibration u_{B3} and the calibration artifact resolution u_{B4}, with respective sensitivity coefficients c_{Bi}, for i=1…4. The combined measurement uncertainty is calculated as:

$$u_c = \sqrt{\sum_{i=1}^{n} c_i^2 u_i^2} \quad (1).$$

The expanded uncertainty is calculated as:

$$U = ku_c \quad (2)$$

with coverage factor k=2, for probability of 95%.

Monte Carlo is an alternative method to mainstream GUM. This method is based on random selections, hence the name of the method. The Monte Carlo method allows to compensate for the shortcomings of the GUM, such as:

- when nonlinearities appear that cannot be represented by the assumptions of the GUM,
- when calculating according to the GUM, a normal distribution is always assumed for the probability density of the output quantity.

However, if there are significant deviations from the normal distribution, GUM will not provide an adequate representation. The Welch-Satterwhite method, [21] can be used to calculate the effective degrees of freedom, which makes the output distribution appear with a t-distribution, thereby reducing the influence of deviations from an ideal distribution. Despite this, in reality much larger errors can be encountered, in which case the only option is the Monte Carlo method:

- when one of the uncertainty contributions is significantly larger than the others,
- when the order of magnitude of the output quantity is the same or close to the uncertainty.

The Monte Carlo method consists of propagation of distributions, as opposed to GUM, where propagation of uncertainties is performed, as shown in Figure 1.

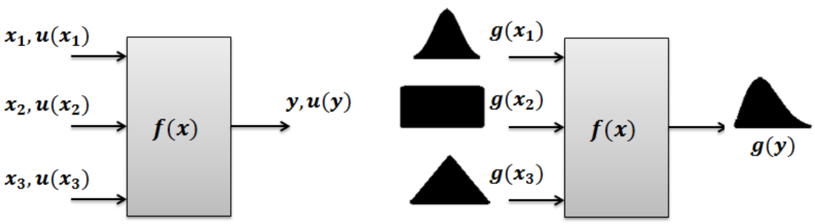

Fig. 1. GUM Uncertainty Propagation (left) versus Monte Carlo Distribution Propagation (right)

The Supplement 1 of GUM 101:2008 [16], provides the steps to perform a Monte Carlo simulation:

1. defining the measured and input variables,
2. modeling,
3. estimation of the propagation of the input distributions,
4. simulation calculation and
5. presentation of the results.

When calculating a Monte Carlo simulation, a certain number of simulations should be performed. Each simulation generates a random variable depending on the distribution of the input variable. The number of necessary simulations to be performed is determined as:

$$M > \frac{10^4}{1-p} \tag{3}$$

where, M is the calculated number of simulations, and p is the required probability. For example, for a probability of 95% p=0.95, the number of simulations is equal to 200000. In most cases, when using Monte Carlo, 10^6 simulations are used. The higher the number of simulations, the better the result, but a balance needs to be made because the higher the number of simulations, the more processing power is required on the machine on which they are calculated.

III. MONTECALC UNCERTAINTY TOOLKIT-DESCRIPTION

LabVIEW™, [17] is graphical programming language allowing options on developing virtual instrumentation from the appearance of the user interface to the program structure. A good virtual instrument must have the following features:

- scalability: a measure of how easily a program can be extended to perform more tasks,
- maintainability: adding new features to a program without reprogramming, and
- readability: a measure of how easy it is to review a program and understand its function.

With LabVIEW, modular programs are developed, that is, the problem is divided into smaller parts (modules) that perform a specific function, and the following issues should be taken into account:

- coupling of the modules, and
- cohesion: a measure of how well a module performs a function.

The virtual instruments should have low coupling and high cohesion of modules. In a nutshell, a module should be so good at performing one function that it does not need to perform anything else. The originally developed program MonteCalc Uncertainty Toolkit is packaged in a folder with appropriate drivers, and is in the format of an .exe file, which allows it to be used without installing the entire LabVIEW™ package. When the .exe file is launched, the Set-Up window shown in Fig. 2, opens.

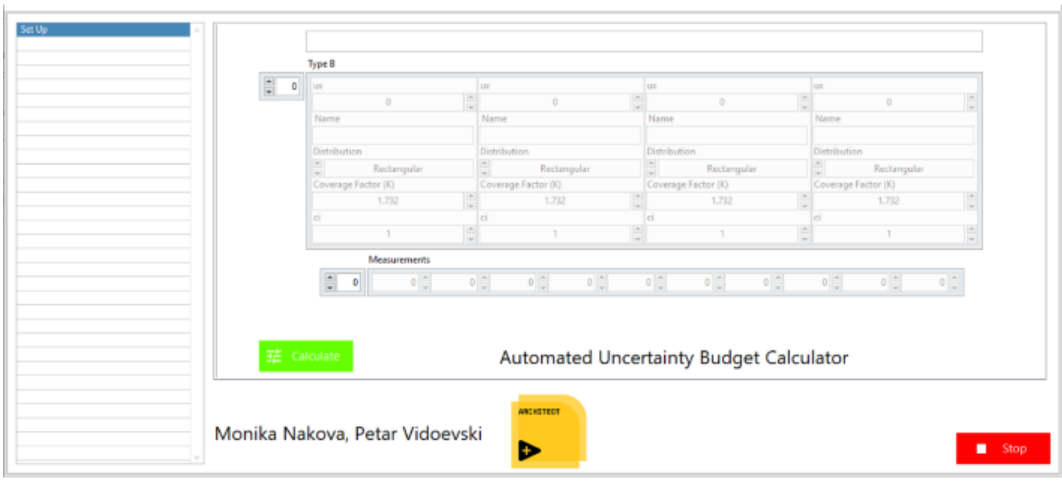

Fig. 2. MonteCalc Uncertainty Toolkit set-up window

This window has the following functionalities:

- entering a calibration name,
- entering Type B components,
- entering measurement results (the number of measurements and Type B components that can be entered is practically unlimited),
- starting the calculation and
- ending the program.

By pressing the Calculate button, two new virtual instruments are automatically created and the measurement uncertainty budget is calculated according to the GUM and Monte Carlo simulation. The new virtual instruments are named GUM _ Calibration name from Set UP and MonteCarlo _ Calibration name from Set Up. The names of the new instruments are added to the List control. When the corresponding name of the List control is clicked on, the corresponding front panel is displayed on the Split Panel. The virtual instrument for calculating the measurement uncertainty budget, based on the GUM has the following functionalities:

- automatic calculation of the measurement uncertainty budget based on the parameters entered in Set Up,
- automatic calculation of the compliance graphs depending on a limit value that is set with an appropriate control,
- saving results in .jpeg for the compliance graphs and saving the budget in .csv format,
- automatic scaling of the y and x axes of the compliance graphs in order to obtain greater visibility of the results.

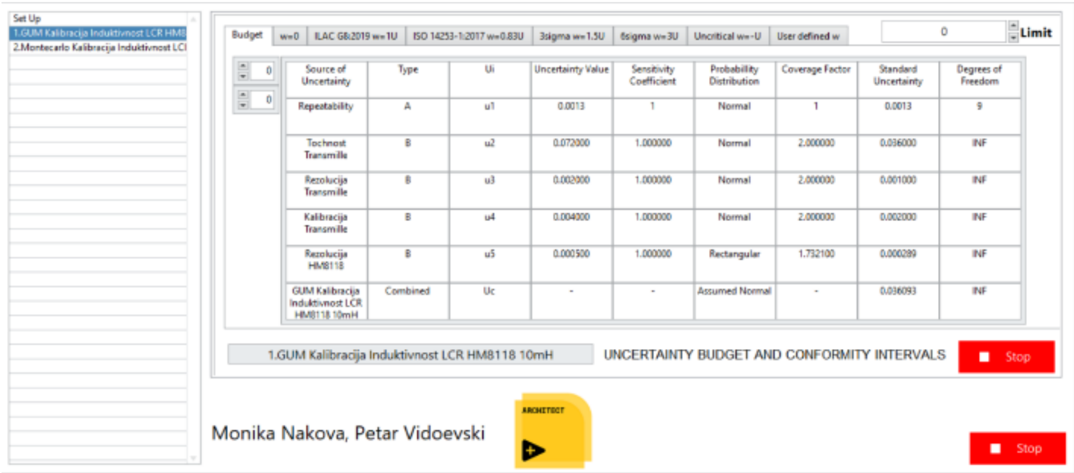

Fig. 3 MonteCalc input of components for calculation of measurement uncertainty budget according to GUM

The virtual instrument for Monte Carlo simulation has the following functionalities:

- automatic calculation of Monte Carlo simulation depending on the parameters entered in Set Up,
- selection of the number of random variables, and distribution partitions,
- automatic calculation of fit graphs depending on a threshold value that is set with appropriate control,
- saving the final distribution and fit graphs in .jpeg format, and the simulation results in .csv and
- automatic scaling of y and x axes of fit graphs in order to obtain greater visibility of results.

The Monte Carlo simulation is performed using a virtual instrument palette that allows the generation of random numbers with an appropriate distribution. The generation of the distribution in this case is done depending on the type B parameters that are entered. For each type B component, a distribution of random numbers is generated and summed together with the type A component. From the summed distribution, the uncertainty for the Monte Carlo simulation is calculated. The MonteCalc Uncertainty Toolkit has also an incorporated complex evaluation module for conformity assessment against different prescribed decision-making rules in line with the international Guideline ILAC G8:09/2019, [18]. The built-in decision-making rules in MonteCalc are the binary rule, the binary rule with guard band, the non-binary rule with guard band and with measurement uncertainty, and other.

IV. CASE STUDY-CALIBRATION OF IMPEDANCE PARAMETERS METER

The MonteCalc Uncertainty Toolkit has been applied on real experimental data derived by the process of laboratory calibration of a RLC meter in LEM. More details on the test procedure are published in [9] and [11].

Figure 4. Calibration set-up for the ROHDE & SCHWARZ HM8118 LCR meter using the Multifunctional Calibrator Transmille 4015 in LEM

In this case study, the LEM calibration procedure of LCR bridges- meters for electrical inductance and capacitance is conducted on the UUT is ROHDE & SCHWARZ HM8118-Programmable LCR-Bridge, with technical specification in [25], by using the LEM reference standard Transmille 4015 [26] and a test set-up as in Figure 4.

V. RESULTS AND DISCUSSION

In Table 1, some of the most specific results obtained from the two approaches (GUM and Monte Carlo), by using the MonteCalc Uncertainty Toolkit are given for the purposes of calibration of a RLC meter at the ranges of electrical inductance and electrical capacitance. Figure 5 graphically displays the result obtained by the MonteCalc software, from the GUM uncertainty evaluation of calibration of the RLC meter at the 10 mH electrical inductance measurement.

Table 1. RLC meter calibration uncertainty results obtained by two approaches GUM and Monte Carlo embedded in MonteCalc Uncertainty Toolkit

Measurement point	Uncertainty GUM	Uncertainty Monte Carlo
Electrical capacitance		
10 nF	0.025 nF	0.15 nF
100 nF	0.18 nF	0.99 nF
Electrical inductance		
10 mH	0.037 mH	0.21 mH
100 mH	0.36 mH	2.1 mH

Also, the limits of the decision-making rule with the binary rule are presented. In all the derived results there is evident discrepancy in the obtained calibration uncertainties at the level of one order magnitude. This is expected due to the deviation from a normal Gaussian distribution, which in the GUM approach is neglected, while in the Monte Carlo simulation it is considered, through the random generation of variables. For these specific calibration cases the application of the Monte Carlo approach is justified, as it provides wider uncertainty, leading to safer decision making in the process of conformity assessment. Other software options for Monte Carlo simulations were analysed, like GoldSim [27] or MatLab/Simulink [28]. After thorough study, it has been concluded that most optimal for this particular case study is the development of the simulation model in LabView. More details on this analysis will be provided in the planned post-conference issue of this contribution.

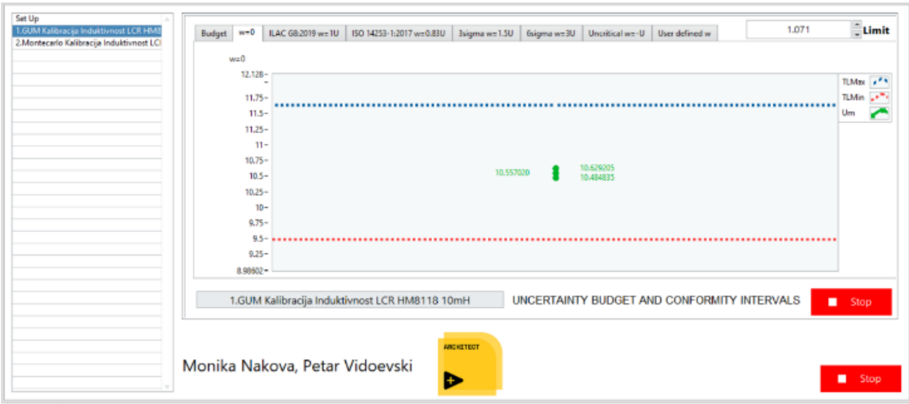

Fig. 5 MonteCalc graphical display of the results of the conformity decision rules obtained according to GUM

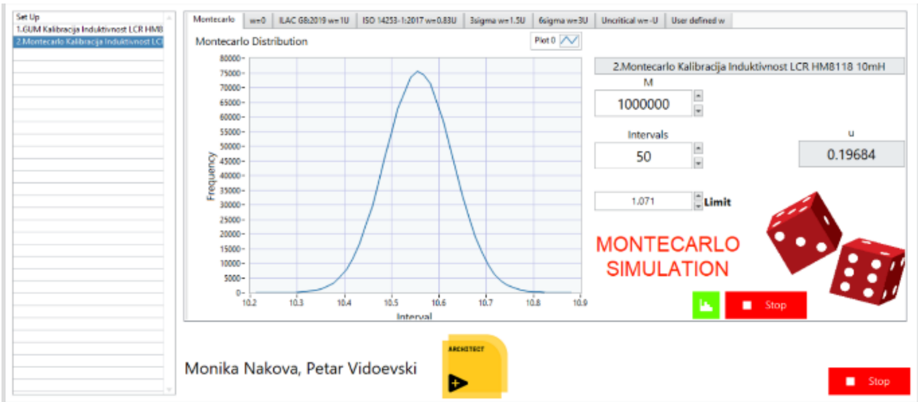

Fig. 5 The probability distribution obtained by simulation with the MonteCalc Uncertainty Toolkit

VI. CONCLUSIONS

In the paper, the original software MonteCalc Uncertainty Toolkit developed in LEM, dedicated for measurements uncertainty evaluation, based on two approaches mainstream GUM and Monte Carlo is presented. The software is validated on a real experimental case of laboratory calibration of RCL meter-instrument for electrical impedance parameters (inductance and capacitance). The derived results are inputs in the decision making procedure according to ILAC G8:09/2019, embedded as module in the MonteCalc Uncertainty Toolkit. The obtained results are satisfactory and verify the developed software package. The MonteCalc Uncertainty Toolkit is universal and can be applied to any case of measurement uncertainty estimation, with no restrictions on the type of instrument, the physical quantity measured, the range, the type probability distribution etc.

REFERENCES

[1] W. D. Sulistyo, W. Deny Yudo, J. Azmi Bin Muhamad @Md., P. Candra Kurnia, and Hartono, "The Effectiveness of Laboratory Digitalization for 21st Century Learning", Int. J. Interact. Mob. Technol., vol. 18, no. 04, pp. pp. 48–64, Feb. 2024.

[2] M. Koval, J. Tesař, S. Schönhals, A. Sharma, D. Balslev-Harder, C. Galvan-Hernandez, H. Baumann, D. Mahovský "Digital Calibration Certificates (DCC): Benefits and Challenges to overcome for implementation", EPJ Web Conf. 323 01001 (2025) DOI: 10.1051/epjconf/202532301001

[3] M. Cundeva-Blajer "Data Fusion for Uncertainty Evaluation in Extreme Electrical Metrology", Proc. of Int. Cong. on Measurement, Quality and Data Science MQDS 2023, 5-7.06.2023, Bordeaux, France

[4] M. Cundeva-Blajer "Data Science for Testing, Inspection and Certification", Proc. of the IMEKO TC11&TC24 Joint International Conference, 16-19.10.2022, Cavtat-Dubrovnik, Croatia, ISBN 978-953-7124-13-7

[5] I. Muzyleva, D. Shishlin, L. Yazykova, P. Dobrynin and S. Ambrosimov, "Implementation of the Concept of "Smart Laboratory" in the Framework of Digitization of the University" 1st Int. Conf. on Control Systems, Mathematical Modelling, Automation and Energy Efficiency (SUMMA), Lipetsk, Russia, 2019, pp. 349-352, doi: 10.1109/SUMMA48161.2019.8947471.

[6] M. Kuster, "A Measurement Information Infrastructure's Benefits for Industrial Metrology and IoT," 2020 IEEE Int. Workshop on Metrology for Industry 4.0 & IoT, Roma, Italy, 2020, pp. 479-484, doi: 10.1109/MetroInd4.0IoT48571.2020.9138200.

[7] International Standardization Organization (ISO), "General requirements for the competence of testing and calibration laboratories", MKC EN ISO/IEC 17025:2018.

[8] K. Demerdziev, M. Cundeva-Blajer, V. Dimchev, M. Srbinovska, Z. Kokolanski, "Improvement of the FEIT laboratory of electrical measurements best CMC through internationally traceable calibrations and inter-laboratory comparisons", In Proc. XIV Int. Conf. ETAI, Struga R. N. Macedonia, Sep. 2018.

[9] M. Cundeva-Blajer, M. Nakova, V. Sapundziovski, K. Demerdziev, Improvement of metrology infrastructure in the area of extreme impedance calibrations, Acta IMEKO, vol. 13 (2024) no. 3, pp. 1-6. DOI: 10.21014/actaimeko.v13i3.1765

[10] M. Nakova, M. Cundeva-Blajer „Extension of the Calibration and Measurement Capabitilities of a Laboratory for Electrical Measurements and Application of the Monte Carlo Method for Evaluation of Measurement Unceratinty", 6th Int. Conf. "Quality and Competence" 26.-28.09.2024, Ohrid, R.N.Macedonia

[11] M. Cundeva-Blajer, M. Nakova, V. Sapundziovski, K. Demerdziev "Extreme Impedance Calibrations: Enhancement of Metrology Infrastructure", Proceedings of the IMEKO TC8&TC11&TC24 Joint Int. Conf., 11-13.10.2023, Funchal-Madeira Islands, Portugal

[12] Marija Cundeva-Blajer "Application of Numerical Methods in Metrology of Electromagnetic Quantities", Jour. of Accreditation and Quality Assurance Vol. 20, Iss. 6 (Series on Advances in Mathematics for Applied Sciences-Vol.86, World Scientific Publishing Co. Pte. Ltd), Springer Berlin Heidelberg DOI 10.1007/s00769-015-1175-7, 2015 pp. 140-148

[13] Marija Cundeva-Blajer, Ljupco Arsov "Prediction of Resistance Standards Time Behaviour by Stochastic Determination of Lagrange Polynomial", Series on Advances in Mathematics for Applied Sciences-Vol.84, World Scientific Publishing Co., 2012 pp. 102-109

[14] M. Cundeva-Blajer, L. Arsov „Computer Aided Techniques for Estimation and Reduction of Electromagnetic Measurement Devices Uncertainties", Int. Journal of Metrology and Quality Engineering, Vol. 2, EDP Sciences, Paris, 2010, pp. 89-97

[15] JCGM 100:2008 with member organizations (BIPM, IEC, IFCC, ILAC, ISO, IUPAC, IUPAP and OIML), "Evaluation of measurement data – Guide to the expression of uncertainty in measurement – GUM".

[16] JCGM 101:2008 "Supplement 1 to the "Guide to the expression of uncertainty in measurement" - Propagation of distributions using a Monte Carlo method"

[17] "LabVIEW Programming Reference Manual", National Instruments Corporation, 2024

[18] ILAC-G8:09/2019 "Decision Rules and Statements of Conformity"

[19] W. K. V. Chan, Ed., "Theory and Applications of Monte Carlo Simulations". InTech, Mar. 06, 2013. doi: 10.5772/45892.

[20] P. R. Guimaraes Couto, J. Carreteiro, and S. P. de Oliveir, 'Monte Carlo Simulations Applied to Uncertainty in Measurement', Theory and Applications of Monte Carlo Simulations. InTech, Mar. 06, 2013. doi: 10.5772/53014.

[21] Spellman F, Whiting N. Handbook of Mathematics and Statistics for the Environment. Taylor & Francis; 2014

[22] M. Nakova, M. Cundeva-Blajer, K. Demerdziev "Development of a Procedure for Decision Making Rules for Conformity of Results in Calibration of Electrical Inductance Meters", Int. Conf. MakoCigre 2023, 17-19.09.2023, Ohrid, North Macedonia

[23] N. Sakamoto, "Long-term calibration results of 10 mH and 100 mH standard inductors using a reactance compensation method," CPEM 2012, Wash. DC, USA, 2012, pp. 582-583, doi: 10.1109/CPEM.2012.6251063.

[24] JCGM 106:2012 "The role of measurement uncertainty in conformity assessment"

[25] Rohde&Schwarz, "*HM8118 LCR-Bridge User Manual*", Rohde&Schwarz, München, Germany, 2016.

[26] TRANSMILLE LTD, "Transmille 4000 Series Advanced Multiproduct Calibrator, Operation Manual", 2015

[27] https://www.goldsim.com/Web/Home/ (accessed 24.05.2024)

[28] https://www.mathworks.com/ (accessed 24.05.2024)