# TRANSFORMING AND PROCESSING THE MEASUREMENT SIGNALS

## VIRTUAL MEASURING INSTRUMENTS AS MEANS OF UNCERTAINTY EVALUATION

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**Abstract.** Modern measuring instruments as highly technological, precise, multi-functional tools today are complex systems, and estimation of their uncertainty turns into a non-trivial task of science. To provide information about the probability of results, their convergence, and reproducibility, it is necessary to analyze the task-oriented measurement uncertainty. As an approach to determining the uncertainty of complex systems, to avoid the need for professionally experienced personnel and expensive "artifacts" used for evaluation, there is a method of a so-called virtual measuring instrument. In this method, the measurement process is simulated, taking into account the influence of the main disturbance parameters and conducting statistical analysis using the Monte Carlo approach. All characteristics of virtual modules repeat the properties of real devices but allow quick and qualitative evaluation of environmental parameters' effect on the accuracy, as well as the uncertainty of measurement. It allows us to evaluate the correctness of the result under the present conditions. The measurement uncertainty is usually caused by several major sources. Uncertainty depends on the method of measurement, but there are still common factors, i.e. uncertainty caused by measuring instruments, methods, operators, and environment. Among environmental influences, it is important to highlight – the change of light and temperature, which can vary widely variate at the production process, and at the same time have a crucial impact on the uncertainty of measurement. The paper presents a virtual measurement instrument method and its known implementations.

**Key words:** WVirtual measuring instrument, Uncertainty evaluation, Simulation and statistical analysis of measuring uncertainty, Monte Carlo method, Coordinate-measuring machine.

### 1. Introduction

Measurement uncertainty evaluation is a basic requirement for a high-quality and cost-effective production process and includes a certain technological approach. However, in coordinate metrology, the estimation of measurement uncertainty is a complex process. It requires a specialist performing the analysis to make certain adjustments for each case. Features of size, shape, shape deviation and the aspect of accessibility when a measure is made without changes made from the outside have a significant impact. Thus, the big range of parts types with several variations of shape and at the same time the presence of small tolerances require the use of simple but effective and at the same time quite universal methods. According to [1-3], there are three different approaches to estimating the uncertainty of measurement results – analytical uncertainty budgets, experimental determination, and computational modeling. All these approaches require an adequate mathematical model and an appropriate description of the quantitative estimates of the uncertainty components.

Estimation of measurement uncertainty using an analytical approach (or uncertainty budget) is based on a detailed description of the error components. The calculations are made according to the method described in the guidelines for measurement uncertainty [1, 4]. The experimental procedure complies with ISO 15530-3 [2], according to which it is necessary to perform multiple measurements of the calibration body. ISO / TS 15530-4 [3] describes general requirements for modeling methods. Numerical modeling is an effective and flexible way to estimate measurement uncertainty in coordinate metrology. This approach is described in the appendix to the guidelines for the measurement uncertainty [5].

It should be emphasized that there is a difference in the understanding of the term "virtual measuring instruments" in Ukraine and abroad. Ukrainian scientists call a computerized tool "virtual" [6, 7]. On the contrary, the developers of the virtual CMM from the National Metrology Institute of Germany, PTB call a computer program for the measurement result in uncertainty determining – a virtual measuring instrument (VMI) [8].

Unlike a computerized instrument, in which a real measurement takes place, VMI simulates the measurement process itself to predict the influence of error factors using multiple measurements. The output is similar to the output data of the real measuring instrument, and the input data reproduce the characteristics of the measured object as if they were measured by a real measuring instrument (MI). The VMI measurement process replicates the MI process (Fig. 1).

The real and virtual branches are connected by three aspects. First, the output data of the real measurement is the input data for the virtual measurement. Second, in real and virtual measurement branches, the inverse problem is solved using the same methods, the parameters of which are equally applicable to both branches. Third, the measurement correctness is verified by comparing the real measured object and the virtual object model.

A real MI evaluates and registers specific object characteristics. Their parameters are obtained from the solution of the inverse problem. As a result of this process, we obtain a model of the measured object and its characteristics. Since the object model is obtained with a certain uncertainty, it is then necessary to calculate this uncertainty. This uncertainty can be obtained using the VMI. The creation of the object model provides the ability to create a virtual model, which in turn serves to form a virtual object. The virtual object is then used to generate virtual measurement data and solve the inverse problem. The next step is to compare the real and virtual model measurement and estimate the uncertainty. In case of divergence between the models, the inverse problem is solved using other parameters or another computer method. A new real re-measured and recreated virtual measurement model is created.

Note that the agreement of real and virtual models must be guaranteed at the first stage of VMI creation. Further, the model can be adjusted by other influential factors, but the first validation guarantees the agreement of the model and real measurement. With unknown input parameters, the use of verified VMI guarantees the correctness and repeatability of the MI measurement process in general [9].

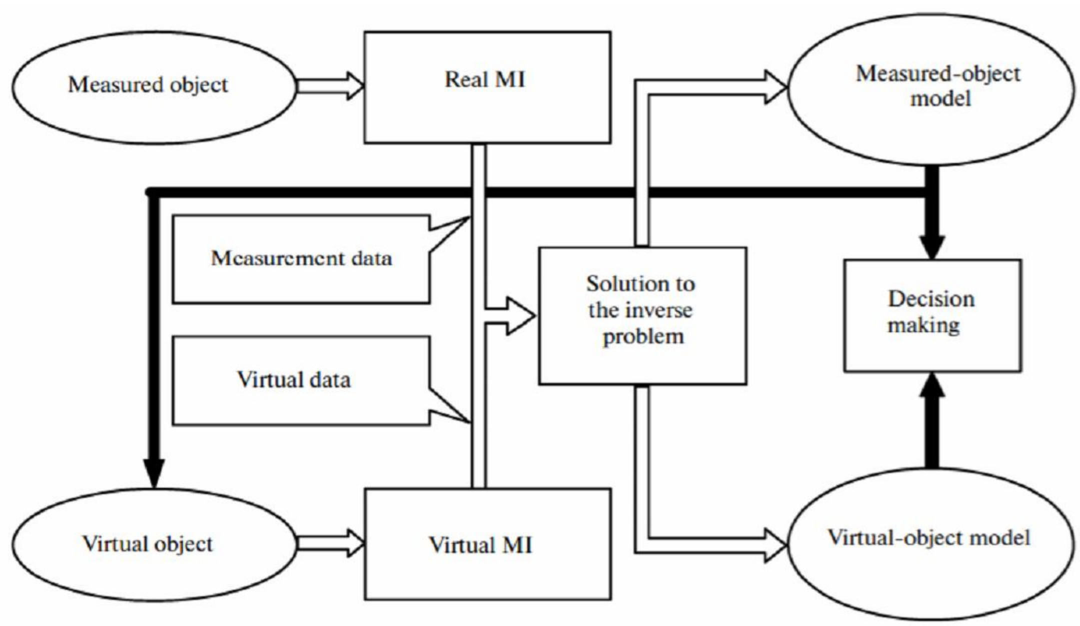


*Fig. 1. A general characteristic diagram that describes the real and virtual MI [9]*

## 2. Goal of work

The aim is to create a virtual measuring instrument basing on the existing approaches and identify its structure for the uncertainty evaluation.

## 3. VMI creation approaches

To date, there are two approaches to the creation of VMI – imitation, and simulation [10]. The imitation is based on the modeling of certain basic processes that occur in the real MI in the measurement process. In other words, imitation is MI operations modeling. The simulation is based on information modeling, i.e. the signal obtained in the process of measuring MI. Unlike imitation, the simulation does not model the MI. The VMI program is based on static modeling using the Monte Carlo method [11]. Due to [9] it is necessary to fulfill three prerequisites for simulation, as more complex in terms of modeling, namely:

1) With the use of modern personal computers, the duration of information generation should not be too long, it should take no more time than the actual MI.

2) The number of independent random numbers generated by the generator must be sufficient to achieve the goal.

3) The method that uses the Monte Carlo approach must correctly reproduce the work of the MI.

Where one of these requirements is not met or are not fully satisfied, then the simulation method can not be used to create VMI. These requirements would be discussed in detail further.

**The data set generation duration**. Simulations using the Monte Carlo method are traditionally used to simulate MI measurement processes. But it should be noted that the Monte Carlo method is one of the slowest computer methods. Today, due to the demand of the crypto industry for powerful computers and the random numbers algorithms modernization, assist in model engineering problems. Analysis of modern pseudo-random numbers generators [12], implemented on a laptop Ivy Bridge i7 with a frequency of 2.6 GHz, showed a large generation speed increase for $\mathbf{10^9}$ numbers by the modern algorithm Xoshiro256 + when compared to the classic Mersenne Twister. Generation of this amount of pseudo-random numbers took 1,279 seconds compared to 4,522 seconds with the classic Mersenne Twister. Therefore, the speed of random number generation algorithms increases, which improves the applicability of the simulation.

**The number of random numbers. Periodicity.** The Monte Carlo method involves the use of a large array of random mutually independent numbers. One of the disadvantages of previously developed algorithms is the presence of so-called periodicity. The periodicity as the repeatability of the results of the random number generator is about 30 million [9]. In the case of the simulation of the work of, for example, a scanning electron microscope (SEM), the required number of independent numbers can be 600 billion [13]. Today, the frequency of the most used and fastest generators starts from 264 and reaches 232830 [14]. Thus, it can be argued that the frequency of the generator is satisfactory for the simulation of SEM.

**The application of the Monte Carlo method** depends on the fulfillment of previously established conditions and does not always require MI modeling. You need a computer program that will provide data identical to the data obtained by the actual MI. The uncertainty estimation program (UEP is an analog of the VMI) is based on computerized mathematical models of the measurement process. In this model, the measurement process is presented completely, from measurement to record the result, taking into account all influencing factors. In the simulation, these factors vary within acceptable values (described by their respective distributions), and the process of a virtual measurement is repeated many times, using different combinations of influencing factors. Uncertainty is determined as a variation of the virtual measurement final result [3].

**Reasons for numerical simulation using**

One of the reasons for using numerical simulation instead of the classical approach is the number of sources of uncertainty. For example, when using a coordinate measuring machine (CMM), experts from the National Metrology Institute of the United Kingdom – NPL especially highlight the spatial and computational sources of uncertainty [15].

*Spatial error* is the error in measuring the coordinates of a point on the surface of the measured body and is determined by the following components:

- accuracy of manufacturing CMM components – guides, scales, probe system, and reference sphere used for metrological verification;
- the environment in which CMM operates, namely: temperature values, its gradients, humidity, and vibrations;
- measurement strategy – sampling value and direction, probe stylus type and measurement speed;
- measured object characteristics – elasticity, surface roughness, hardness, and weight of the component.

The *calculation error* is the error of estimation the shape deviation and measured object size, which is determined by:

- CMM software that estimates the geometry of the object;
- numerical accuracy of the CMM computer;
- the number and positioning of measured points;
- the extent of geometric shape deviation from the ideal.

Geometric deviations of CMM are usually measured directly using laser interferometers and specialized optics or indirectly using sequential multi-position laser measurement [15]. Having determined these deviations, we then use them to adjust the measurement, the so-called computer-aided accuracy. According to [15], 21 kinematic error sources are taken into account for CMM. Kinematic errors occur due to parts manufacturing imperfections or due to the adjustment of machine elements.

Each of these errors is carefully identified and forms the corresponding part of the CMM error map following the measurement scheme and sources of uncertainty of the machine (Fig. 2). Unfortunately, there is also uncertainty in measuring these geometric deviations. This means that the coordinate axes are also entered with uncertainty. Measurements using CMM involve the presence of many contact points and several calculations. Uncertainty in the coordinates of each measured point affects subsequent measurements and the uncertainty of measuring the part as a whole.

**International standard and regulations for VMI**

The evaluation of uncertainty when using a virtual measuring instrument is based on ISO/TS 15530-4:2008 Geometrical Product Specifications (GPS) — Coordinate measuring machines (CMM): Technique for determining the uncertainty of measurement — Part 4: Evaluating task-specific measurement uncertainty. It suggests using simulation as a basis (both for the user of CMM, and the manufacturer) for measurement uncertainty estimation applications (simulations) using CMM. The standard also offers methods for testing such applications, describing the advantages and disadvantages of these methods. Finally, various test methods to determine the uncertainty for specialized measurements (uncertainty related to specific measurements and specific measurement methods), using modeling for CMM measurements, taking into account the measuring device, environment, measurement method, and object of measurement are described. This document describes the general functions without limiting possible technical implementations.

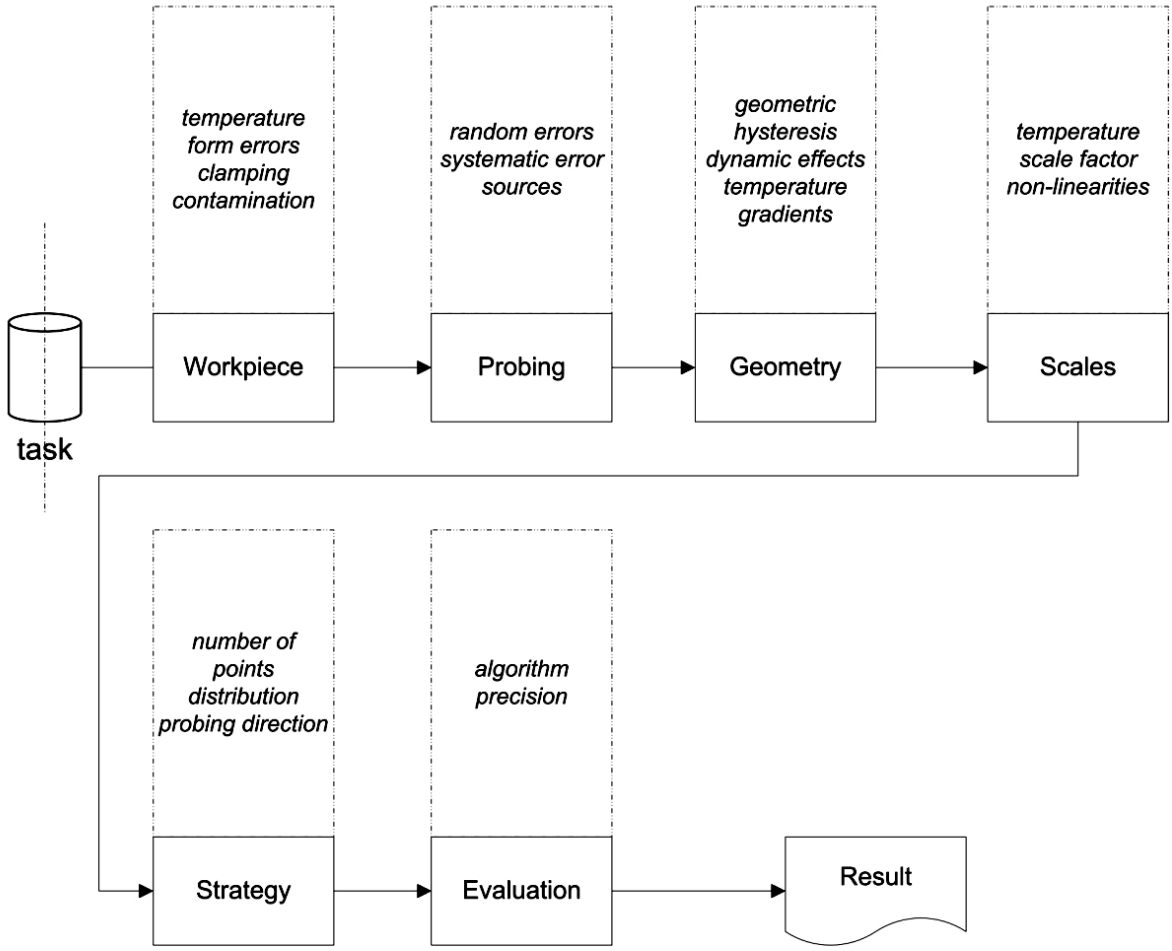


*Fig. 2. Block diagram of the CMM measurement process (Adapted diagram B.1 ISO 15530-4) [3].*

Guidelines for verification and evaluation of developed packages are included in the standard.

The uncertainty estimation program repeats hundred of times the virtual measurement of an object (Monte Carlo method), each time changing the influence factors and characteristics, and a variable set of input data. The input data largely depends on the uncertainty of the CMM geometry and its effect on the error map. Two types of virtual CMM have been defined: online and offline. If the estimation is performed similarly to the processing of real data, using the same software package as the real CMM, the same sequence of estimation operations as in the real measurement (including the same system for detecting the stylus and its size, including the object orientation system), then the virtual CMM is defined as online. If third-party software is used that is not used in the actual measurement process and the measurement simulation processing sequence is only similar to the real one, such virtual CMM is defined as offline. Thus, summarizing the standard for VCMM for all VMI, the tool imitation can be called offline VMI, and the simulation model based on the data obtained by real MI in its process an online VMI. We will also use the explanation of the virtual CMM proposed by the German National Metrological Institute PTB, namely part 2 (Traceability of Coordinate Measurements for virtual measuring machines) [16], namely:

1) Virtual CMM uses a coordinate measurement sequential simulation with accurate simulation of elementary contributions to the uncertainty for each of the test points.

2) There are three main types of contributions, namely: known systematic (which may not always be known to the user), unknown systematic (reproducible only in a short period), and random contributions.

3) The estimation of the coordinates obtained in the simulation process should be as close as possible to the estimate of the real coordinates.

4) The simulation is repeated a statistically significant number of times.

All known systematic contributions remain unchanged, all unknown systematic contributions change in each simulation, taking into account the assumptions about their distribution and limits. After each simulation, the difference between the actual measurement and the values obtained during the simulation is calculated. After the required number of virtual experiments, a statistical evaluation of the results is performed. Finally, the extended uncertainty U for (k = 2) is included in the measurement report [15]. Modeling using the Monte Carlo method, the mathematical basis of uncertainty estimation programs, is described in the Appendix to the Representation of Uncertainty in GUM Measurements [5]. It suggests using contribution distributions and a mathematical measurement uncertainty estimation model and its implementation by the Monte Carlo method. This method assumes an arbitrary number of input values, but the output is only one value. The described method is a practical and effective alternative to the approach to uncertainty proposed in GUM.

**Examples of VMI implementation**

Consider the implementation of VMI on the example of a typical CMM. The primary task is to estimate the residue field, usually performed by the manufacturer. This requires an artifact, for example, a plate with round holes, ideally made of a material with a low coefficient of thermal expansion. This plate, in turn, is measured in six configurations. Typical measurement directions are parallel to the XY plane (two heights), the XZ plane (measurement on both sides), and the YZ plane (measurement on both sides). The next step is to measure the temperature gradients around the CMM. Finally, it is important to describe the kinematic chain, i.e. the sequence of moving axes. With this information, the VMI program simulates a real CMM. In practice, it is necessary to provide data on the test system calibration, and the measured object thermal changes uncertainty. Then the program simulates (100 – 200 times) on VMI, changing each time the input data, the contributions of the machine, the environment.

Today, the commercially available MegaKal virtual CMM package can be integrated into the Zeiss CMM software environment from Leiss and Quindos from Leitz [15]. The program is installed on the CMM computer and works simultaneously with the measurement (online). The input parameters for the program are geometric errors, probe errors, measurement strategy, and test points. Geometric errors and probe errors are determined experimentally using the Kalkom program [15]. Measurement strategy and test points are imported from the CMM program. The advantage of this approach to modeling using the Monte Carlo method is its one-time execution, as long as the measuring conditions for the part do not change. An important advantage of this method of estimating uncertainty is the possibility of its implementation without a real experiment. In this way, you can choose the number of measurement points, the configuration of the stylus to ensure the best measurement. Virtual measuring instruments have come a long way to ensure traceability of measurement and today's work to add scanning and rotary tables is going [15].

There were attempts to create VMI not only for CMM but also for other means, such as the scanning electron microscope [10, 13, 17-19]. In the process of virtual SEM development, it was found that it is impossible to create a program based on the simulator due to the complexity of the calculations, but a program based on the simulator was created and experiments were conducted on its application. The development of VMI is envisaged for other branches of science and technology [20]. The importance of creating virtual tools is also indicated by the opening of a center for the study and training in the field of VMI at the National Metrological Institute PTB (Germany).

## 5. Conclusions

Nowadays, the virtual measuring instruments form the underpinning pillars for the estimation of the uncertainty of coordinate measuring machines. Rapid determination of measurement uncertainty makes it possible to qualitatively train specialists in this field, clearly showing the advantages and disadvantages of different measurement strategies. It provides an opportunity for qualitative estimation of measurement uncertainty under various conditions, using a different number of points, stylus configuration, and measurement speed. Research and implementation of virtual measuring instruments for the digital microscope is our permanent issue. After the analysis of the VMI creation regulations, the decision had been made to apply the ISO/TS 15530-4: 2008. This standard provides a measurement uncertainty estimation methodology using models based on instrumental component, environment, measurement methodology, and measuring object. It was decided to apply the simulation approach for the creation of the VMI. To estimate an environmental impact, it needs within the current model to consider the impact of light, humidity, dust, and vibration factors.

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