

# **Uncertainty evaluation using a Monte Carlo method**

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# Guide to the Expression of Uncertainty in Measurement

## Supplement 1

### Propagation of distributions using a Monte Carlo method

AIM: to overcome some of the limitations of the GUM, especially when an interval of confidence with a stipulated coverage probability is needed.

## Formulation stage (common to both GUM and Suppl. 1)

You decide a model

$$Y = f(X_1, X_2, \dots, X_N)$$

in which each of the input quantities  $X_i$   
(assumed for simplicity to be uncorrelated)  
and the output quantity  $Y$  are treated as  
random variables.

# The GUM Method

One seeks for the following items of information

- An estimate  $x_i$  for each input quantity  $X_i$
- Its standard uncertainty  $u(x_i)$

You “propagate”  $x_i$  and  $u(x_i)$  by using

$$y = f(x_1, x_2, \dots, x_N)$$

and

# The GUM Method

$$u^2(y) \approx \sum_{i=1}^N \left( \frac{\partial Y}{\partial X_i} u(x_i) \right)^2$$

This is a first-order approximation, good under weak conditions:

- The non-linearity of  $f$  to be negligible compared to the magnitude of the uncertainties.
- The probability density function (pdf) of each  $X_i$  to be symmetric about  $x_i$ .

## The GUM Method

- In many cases one needs  $U_p(y)$ , where  $p$  is a prescribed coverage probability.
- In these cases more knowledge is necessary than simply the first ( $x_i$ ) and second ( $u^2(x_i)$ ) moments of  $X_i$ , namely

The pdf of  $Y$ .

# The GUM Method

- The Central Limit Theorem helps, under rather strong conditions (GUM, G.2).
- If the conditions are met, then  $(y - Y)/u(y)$  behaves like a Student's  $t$  distribution with  $\mathbf{n}_{eff}$  degrees of freedom, where  $\mathbf{n}_{eff}$  is determined with the Welch-Satterthwaite formula (GUM, G.4).

## The GUM Method. Limitations

They are mostly in the determination of a coverage interval:

- If the conditions of the Central Limit Theorem are not met, other ways (e.g., analytical) must be explored. Little guidance is given in the GUM, only for a particular case (dominant uniform).
- The assignment of degrees of freedom to Type B evaluations looks “artificial”.

## The GUM Method. Limitations

They exist also in the evaluation of the standard uncertainty, when:

- The input quantities are strongly asymmetric (e.g., cosine error).
- The measurement model is strongly nonlinear, or so complicated that the derivatives are difficult.

## The Supplement 1 approach

- Instead of propagating only first and second moments of the input quantities  $X_i$ , their pdfs are propagated through the model.

The method is more demanding in terms of amount of knowledge. One has to assign a pdf to each input quantity, based on the experimental data or other knowledge. Guidance is given on the assignment of a suitable pdf.

## The Supplement 1 approach

Problem: given the pdfs of the  $N$  input quantities, find the pdf of the output quantity.

Solution 1:

Analytical, using the Jacobian method (see any textbook on mathematical statistics). A closed-form solution can be found only in the most simple (and therefore uninteresting) cases. In general, the integrals involved in this solution must be solved numerically. Not viable.

## The Supplement 1 approach

Solution 2 (the one adopted in the Supplement):

- Purely numerical, by means of a numerical simulation.
- Method selected: Monte Carlo.
- Tools: suitable random number generators for the various pdfs, reasonable computing power.
- Outcome: a numerical approximation for the output distribution.

## The Supplement 1 approach

- From the numerical approximation for the output distribution, the required statistics, such as the best estimate for the measurand, its standard uncertainty, and the endpoints of a prescribed coverage interval can be obtained.

## The Supplement 1 approach

The method in a nutshell:

- From each input pdf draw at random a value  $x_i$  for the random variable  $X_i$ .
- Use the resulting vector  $\mathbf{x}_j$  ( $j = 1, \dots, M$ ) to evaluate the model, thus obtaining a corresponding value  $y_j$ . The latter is a possible value for the measurand  $Y$ .
- Iterate  $M$  times the preceding two steps.

## The Supplement 1 approach

The method in a nutshell (continued):

- Sort the  $M$  values  $y_j$  for  $Y$  in non-decreasing order.
- Use the sorted values to obtain a numerical approximation for the output distribution, in the form of a piecewise-linear function (details in the Supplement).

## A comparison of the two approaches

- The Monte Carlo approach works in a broader class of problems than the GUM approach. In this sense, it is more general.
- Contrary to the GUM, the output distribution in general is asymmetric. Therefore, the coverage interval for a given coverage probability is not unique, and attention must be paid to this issue. Guidance is given in the Supplement.

## A comparison of the two approaches (continued)

- Compared to the GUM, more emphasis is given to the expanded uncertainty (a coverage interval) than to the standard uncertainty.
- The best estimate (as the expectation of the numerical approximation for the output distribution) does not necessarily coincide with that provided by the GUM.
- Also the standard uncertainties do not coincide. The GUM value may be smaller. This is a consequence of the pdf recommended for sampled data (Student).

## A comparison of the two approaches (continued)

- There is no longer any need for degrees of freedom. Actually, this approach is intrinsically Bayesian.

To go back to reality...

*If your experiment needs statistics, you ought to  
perform a better experiment*

(Lord Rutherford)

Or, if you prefer...

*the only statistics you can trust are those you  
falsified yourself*

(Churchill)