

Measurement uncertainty and its effects on data analysis

Applications in imc FAMOS

This document describes how to calculate the measurement uncertainty of your analyses using the imc FAMOS signal analysis software. Furthermore, it explains what needs to be observed and what the benefits are.

imc FAMOS calculates with large data records; the focus here is on the examination of time series with several thousand measured values. With imc FAMOS the effects of measurement uncertainties can be analysed and the measurement uncertainties of results can be calculated for almost every algorithm written as an imc FAMOS sequence. imc FAMOS thereby offers the following options:

- Calculation of the propagation of measurement uncertainties
- Determination of measurement uncertainties of the results of a mathematical evaluation
- Application of signals and interferences
- Analysis of the effect of interference on existing algorithms
- Testing the robustness of algorithms

How precise is the input signal?

This question is not easy to answer, because many different factors affect the measurement. Important factors are, for example: methods, measuring instruments, environment, measuring object and user.

How the user determines the measurement uncertainty of the input signal is up to him, but he must be fully aware that a measurement is never exact. He can estimate the measurement uncertainty or represent it as a model. In a model the individual measurement uncertainty factors are weighted in order to illustrate the measurement setup as realistically as possible. Many documents describe what corresponding models can/should look like in order to determine the measurement uncertainty as accurately as possible. The guideline for this is the "Guide to the expression of uncertainty in measurement" (always referred to below as the GUM). For example, the following temperature curve was measured (Fig. 1). The measurement uncertainty from the noise band can be estimated to be 0.25 °C.

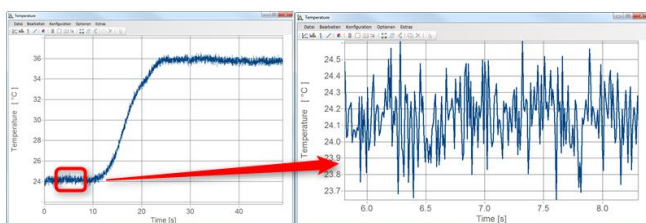


Figure 1

The work of imc FAMOS starts when the measurement uncertainty of the input data is determined. imc FAMOS can now determine the measurement uncertainty propagation beyond the algorithm. It should be noted that the calculated error propagation cannot be more accurate than the measurement uncertainty determined at the beginning.

Determination of the measurement uncertainty of the input data:

A measurement uncertainty is assigned to the input measured value using the command "UncertaintySet()". The input signal is called temperature, for example, and has a value of 27.0 °C. With: UncertaintySet (temperature, "Uncertainty", 0.25) the measurement uncertainty of 0.25 °C is assigned to the input signal "Temperature". If the input signal consists of a time series, the measurement uncertainty of 0.25 °C is assigned to each of the values.

Tailored to the needs of the measurement technician:

imc FAMOS adheres in many parts to the GUM for the calculation of the measurement uncertainties. Beyond the GUM, imc FAMOS offers the user the possibility to use interference variables that are of relevance to the measurement technician, such as noise, mains hum or an offset drift. The assignment is similarly possible using the "UncertaintySet()" function. Hence, voltage peaks can also be applied to a voltage channel (a sine function was measured). The voltage peaks from five passes are shown as an example in Fig. 2. The individual colours represent the voltage peaks of the individual passes here.

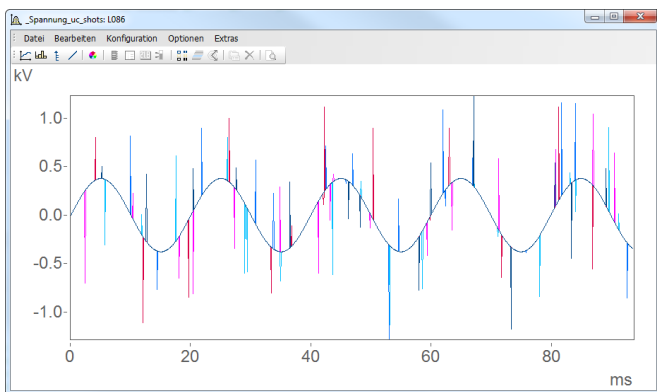


Figure 2

How does imc FAMOS work?

The algorithm to be calculated in imc FAMOS produces results that in turn have a measurement uncertainty. The measurement uncertainty of these results is determined. The Monte Carlo method is used for this in imc FAMOS.

Monte Carlo method in imc FAMOS

The Monte Carlo method (MCM) is based on adding (slight) noise to the input data (0.25 °C or the voltage peaks in accordance with the above examples). Random numbers are applied to the data to simulate the deviations. These deviations take effect as deviations of the results of the algorithm to be calculated. The number of Monte Carlo experiments is statistically evaluated and the measurement uncertainty of the results is determined.

The number of experiments can be entered via the "Uncertainty_LOOP" function. The results of the algorithm are given the user-defined property "Uncertainty"; this is specified as the standard deviation. The mean value is always the value of the first measurement, because no noise has been applied yet in this first step of the Monte Carlo method.

Number of Monte Carlo experiments:

As a matter of principle, a high number of Monte Carlo experiments is necessary to achieve the most accurate result possible. The Monte-Carlo method converges with root M (\sqrt{M}). For a much more stable measurement uncertainty, you need to quadratically increase the number of Monte Carlo experiments.

Example number of Monte Carlo simulations:

However, calculation takes place with time-series data records in imc FAMOS. For example, two temperature measurement series are available, each containing 1,000 measured values. The temperature difference is determined from these two channels. The result itself is in turn a measurement series of 1000 values. It may transpire here that quite a good result is already achieved after $M = 10$ Monte Carlo experiments, because $n = 1,000 \cdot 10 = 10,000$ values are incorporated into the calculation of the standard deviation.

Expanded analyses:

The task is fulfilled with the determination of the measurement uncertainty of the result. Sometimes, however, an explanation is required for the value. The `UncertaintyCalc()` function provides a number of additional analyses that help to understand and interpret the calculated measurement uncertainty. One of these functions is, for example, is the probability density function "pdf0".

The smoothness of the probability density function provides a good overview of whether the number of simulations was sufficient. The graphs in Fig. 3 show the probability density functions for $M = 10, 100, 1000$ and $10,000$ experiments.

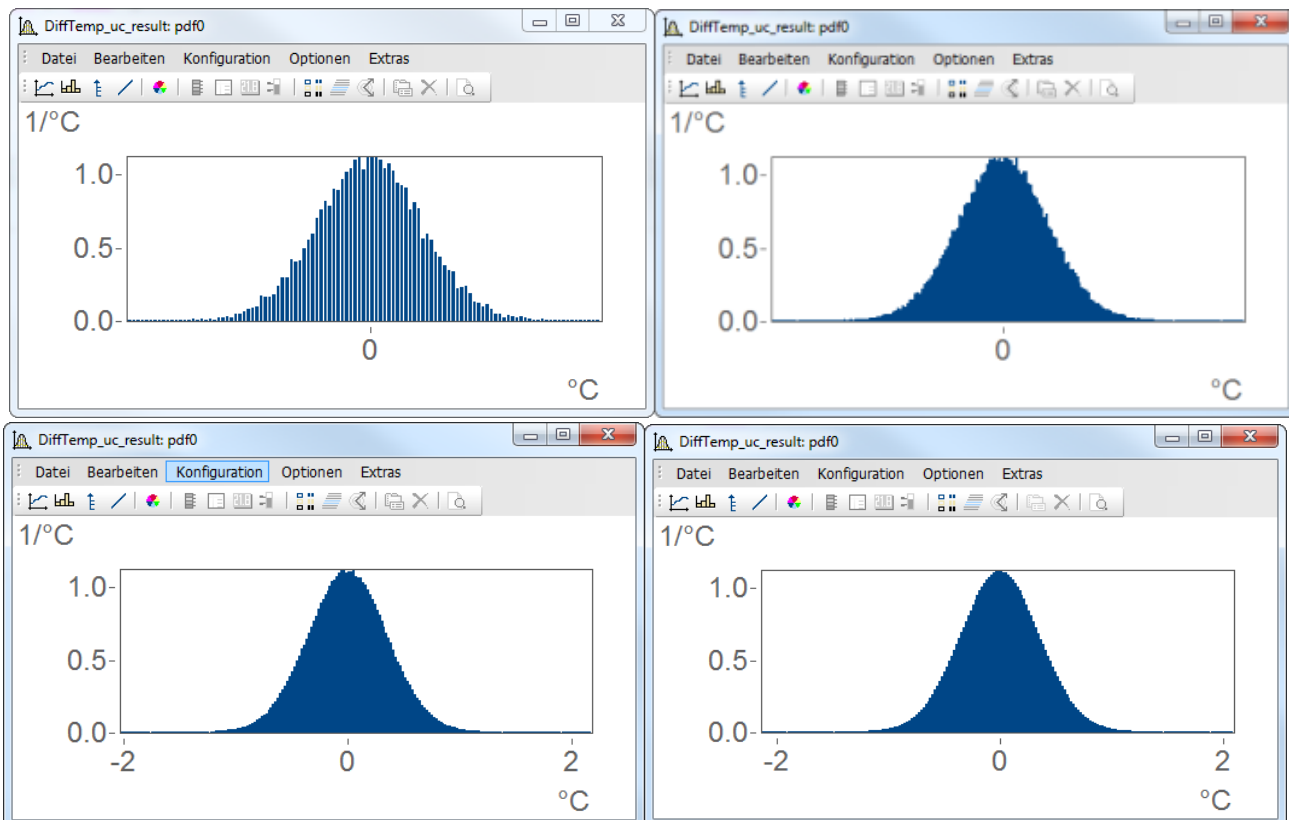


Figure 3

Summary of the individual work steps and calculation example

1. Input data are available
2. A measurement uncertainty is assigned to the input data
3. The algorithm is calculated with uninfluenced input data
4. Uninfluenced results are available
5. Loop of M Monte Carlo experiments
 - a. Noise is added to the input data
 - b. The algorithm is calculated with noisy input data
 - c. The algorithm delivers noisy results
 - d. Iterative calculation of the measurement uncertainty of the results
6. The algorithm is calculated again with uninfluenced input data
7. The determined measurement uncertainty of the results is evaluated

Example:

The rise time is to be determined for the temperature curve shown in Fig. 1.

```

UncertaintySet(Temperature, "Uncertainty", 0.25)
UNCERTAINTY_LOOP 1000
    _Temperature = UncertaintyModify (Temperature)
    _Temperature = smo(_Temperature,1)
    L1 = mean(cut(_Temperature,5,10))
    L2 = mean(cut(_Temperature,30,35))
    RiseTime = pos(_Temperature, L1+(L2-L1)*0.9) - pos(_Temperature, L1+(L2-L1)*0.1)
    UncertaintyCalc (RiseTime )
End
uc = UncertaintyGet( RiseTime, "Uncertainty")
  
```

Explanation of the code:

UncertaintySet() -> assign measurement uncertainty
 Uncertainty_LOOP-> number of simulations
 UncertaintyModify() -> add noise to the measured data
 Smo() -> perform filtering
 RiseTime -> calculate rise time
 UncertaintyCalc-> uncertainty calculation
 uc -> query measurement uncertainty

The result is a measurement uncertainty of 0.07 s which, with a value of 8.6 s, leads to a relative measurement uncertainty of 0.8%.