

EURADOS Training course

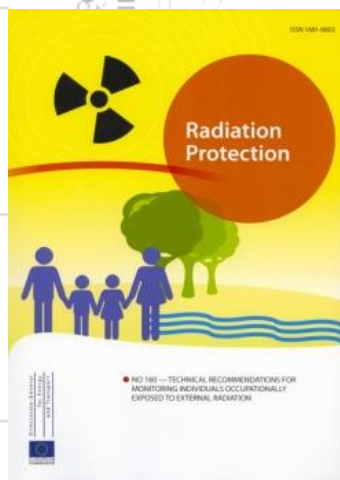
Evaluating uncertainty

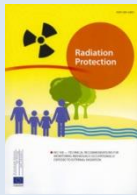
RP160 Chapter 5

Part 2

Janwillem van Dijk

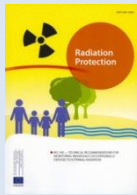
Eurados Training Course
Lisbon, Portugal, 18-22 May 2015





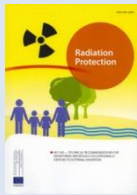
Uncertainty in measurement

- II. The formulation stage and the GUM framework continued
- III. The calculation stage and decision threshold and detection limit



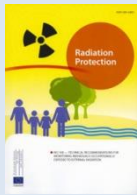
Uncertainty in measurement

- Quantitative measure for *measurement quality*
- Uncertainty is an *a-priory* property of the system (as opposed to error in a measurement)
- Uncertainty evaluation requires to analyze the components of the measurement system



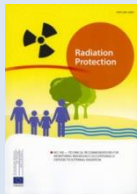
A few more terms

- **Standard uncertainty:** the standard deviation of the probability density function of the measurand
- **95% coverage interval:** the interval around the measured value that with 95% probability contains the true value



A few more terms

- **Decision threshold:** The value above which you can decide that a real dose above background level is observed
- **Detection limit:** The smallest true value of the dose that can be detected with the dosimeter



Stage 1.3 The measurement equation

In mathematical terms:

A function of the input quantities.

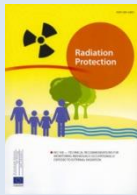
$$x_1, x_2, x_3, \dots, x_N = X$$

$$y = f(X)$$

In practical terms:

A number of formulas used to calculate the dose.

Usually implemented in software.



Stage 2 The calculation stage

Input quantities:

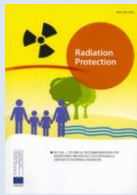
$$x_1, x_2, x_3, \dots, x_N = X$$

Measurement model:

$$y = f(X)$$

Probability density functions for each x_i

$$g(x_i)$$



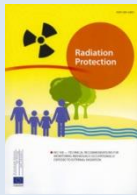
Probability density function of measurand

Probability density function g_y
of the measurand

=

convolution integral of the
joint distribution of g_X

$$g_y(\eta) = \int \cdots \int_{-\infty}^{\infty} g_X(\xi) \delta(\eta - f(\xi)) d\xi_N \dots d\xi_1$$



Probability density function of measurand

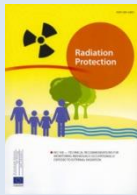
$$g_y(\eta) = \int \cdots \int_{-\infty}^{\infty} g_{\mathbf{X}}(\xi) \delta(\eta - f(\xi)) d\xi_N \cdots d\xi_1$$

↓

$$g_y(\eta) = h(X) \quad \text{Does not exist (in general)}$$

The two main solution routes

1. The GUM framework method, LPU/CLT,
JCGM 100:2008
2. The Monte Carlo Method, MCM,
JCGM 101:2008



Solution routes

1. Use of approximating functions

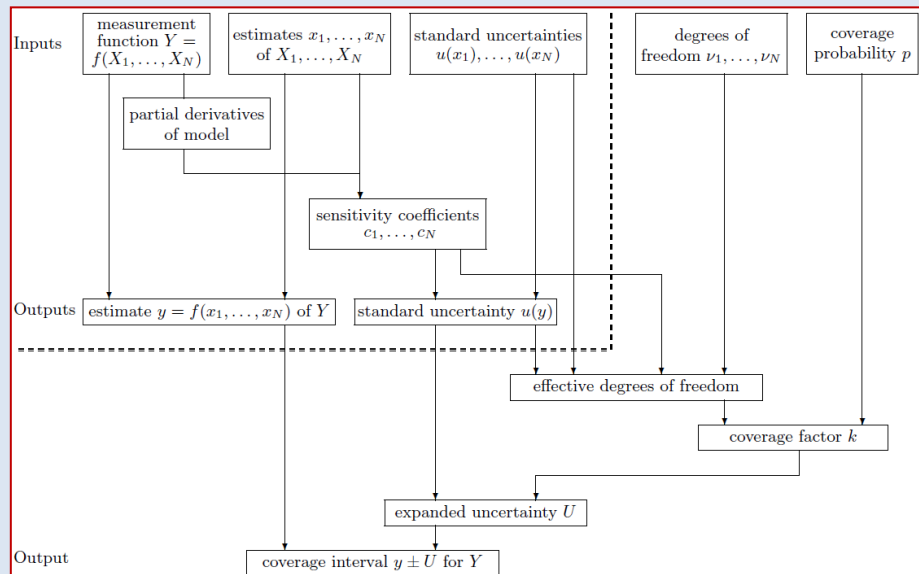
This is the GUM framework method of which the mathematics was developed by Gauß (end 18th century)

2. Use numerical methods

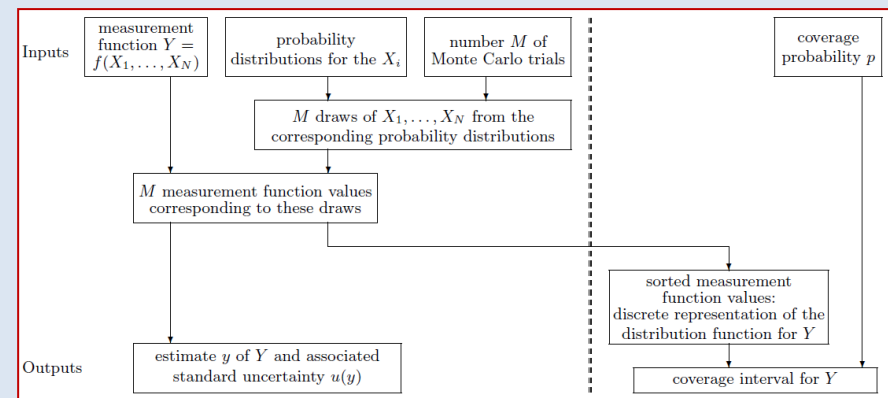
This uses numerical integration based on Monte Carlo techniques (Laplace (1749–1827) reinvented 20th century)

JCGM 104 figures 7 and 8

GUM Framework Method



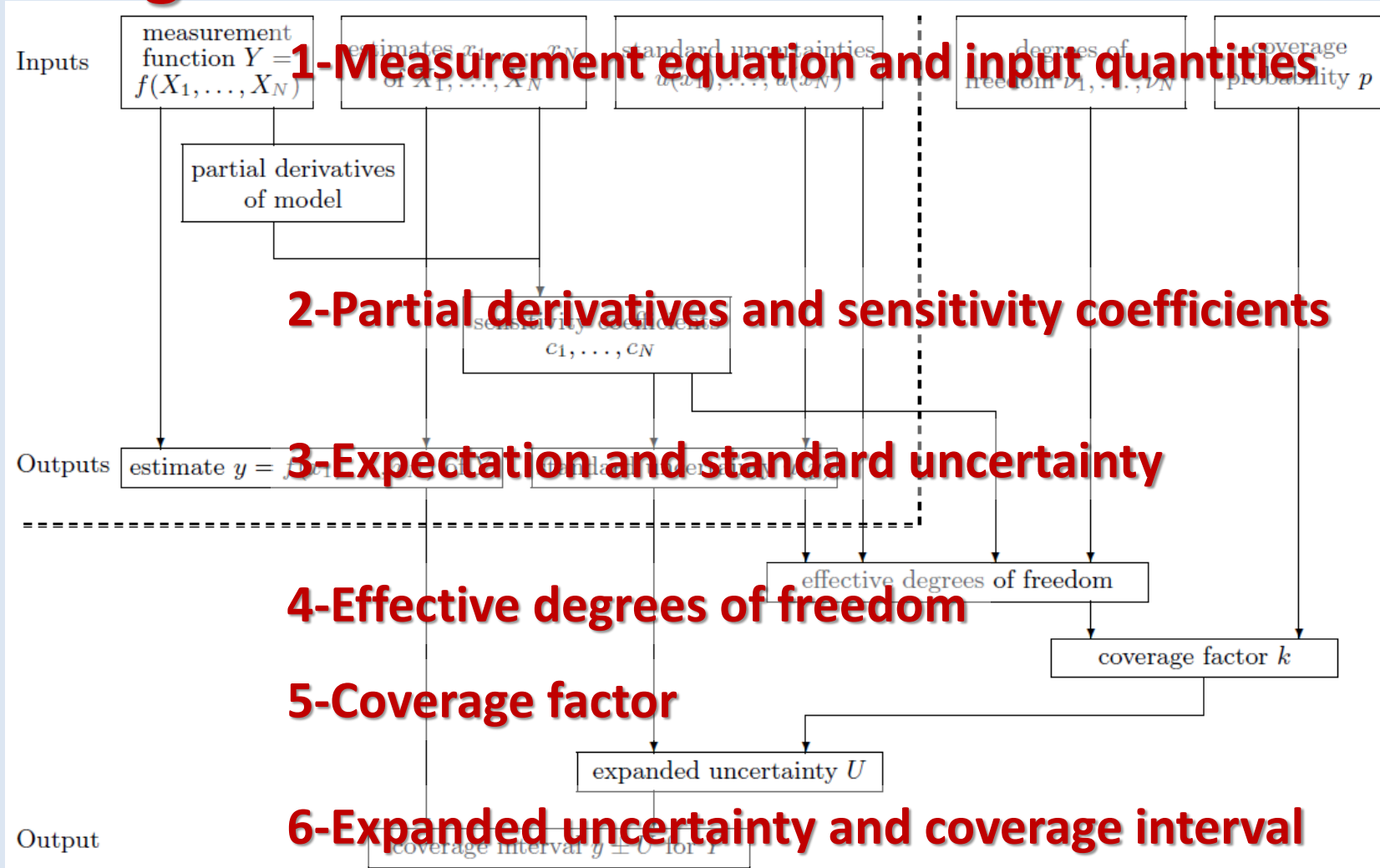
Monte Carlo Method

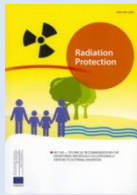


Full uncertainty evaluation until coverage interval

6 steps **4 steps**

Stage 2.1a The GUM framework method





The GUM framework method

Based on the

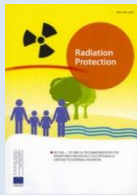
- **Law of Propagation of Uncertainty (LPU)**

$$u_y = \sqrt{\sum (c_i u_{x_i})^2}$$

u_y : standard uncertainty of y

c_i : sensitivity coefficient for x_i

- **The Central Limit Theorem (CLT)**
- **The resulting distribution g_y must be normal (more or less)**



The GUM framework method

1) The input quantities X_i and the measurement equation

$$x_1, x_2, \dots, x_N = X$$

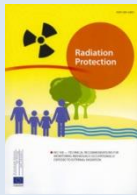
$$y = f(X)$$

measurand = function of input quantities

2) The sensitivity coefficients c_i

$$c_i = \frac{\partial y}{\partial x_i}$$

sensitivity coeff. = partial derivative



Evaluating uncertainty

—EURADOS—▶

1 measurand = f (input quantities)

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

2 sensitivity coeff. = partial deriv.

$$c_i = \frac{\partial f(X)}{\partial x_i}$$

3 LPU : $u_y = \sqrt{\sum (c_i u_{x_i})^2}$

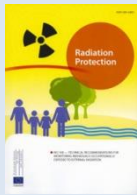
5 expanded uncertainty

$$U = k u_y$$

k : coverage factor

6 coverage interval

$$\hat{y} - U \leq y \leq \hat{y} + U$$



Coverage factor

Calculating the coverage coefficient involves

- The effective degrees of freedom η_i
- The Welch-Satterthwaite formula
(GUM appendix G.4)

For most practical purposes:

$$k = 2$$

Will give the $\approx 95\%$ coverage interval

The GUM framework method

LPU is an approximation

$$y = f(x_1, x_2, x_3) = x_1 x_2 + x_3$$

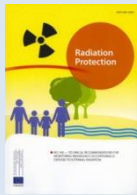
$$c_1 = x_2, c_2 = x_1, c_3 = 1$$

$$u_{y,\text{LPU}} = \sqrt{(c_1 u_1)^2 + (c_2 u_2)^2 + u_3^2}$$

$$\gamma_{y,\text{LPU}} = 0.0$$

$$u_y = \sqrt{(c_1 u_1)^2 + (c_2 u_2)^2 + u_3^2 + u_1^2 u_2^2}$$

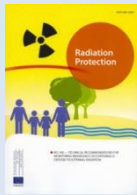
$$\gamma_y = 6 x_1 x_2 u_1^2 u_2^2 / u_y^{2/3}$$



The application

First stage

The formulation stage



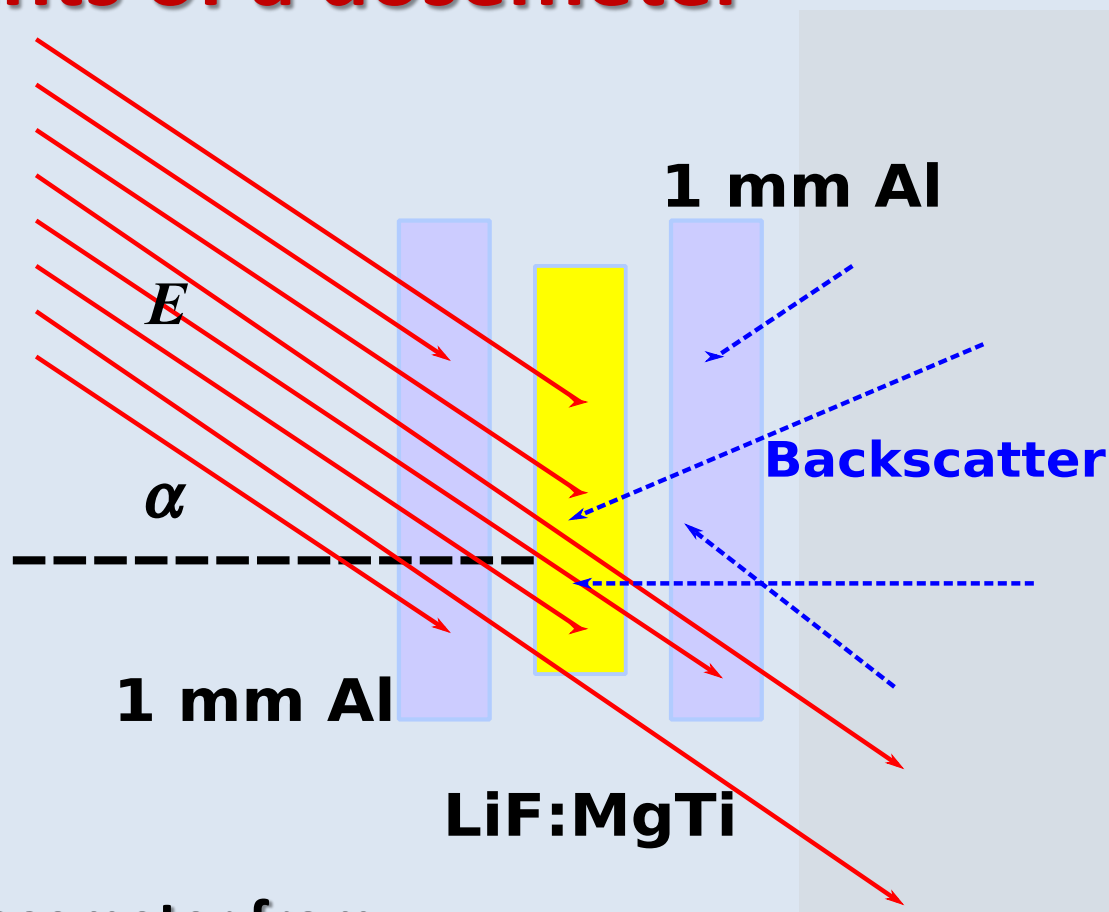
Components of a dosimetry system

- Calibration source traceable to the national standard,
- Evaluation system (reader, developer, ..)
- Reference dosemeters,
- Custom dosemeters,
- Computers with software

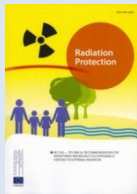
Components of a dosemeter

A very much simplified TL-dosemeter

- Single standard LiF:Mg,Ti detector
- 1 mm Al filter in front and behind

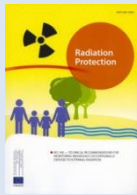


Type test data for this dosemeter from:
Radiat. Prot. Dosim. 54(3/4) 273-277 (1994)



Components of a measurement model

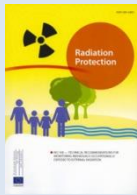
- Sensitivity of the custom dosimeter relative to the reference dosimeter (element correction coefficient, ECC),
- Angle and energy dependency of response
- Sensitivity of the reader determined with reference dosimeter [signal dose⁻¹],
- Background dose,
- Other (environmental) influences



The measurement model

$$x = f_R f_{\text{Det}} (f_{E,\alpha} H_{\text{True}} + f_{\text{Bg}} h_{\text{Bg}}) + z$$

- x : the signal [counts]
- f_R : the reader sensitivity [counts μSv^{-1}]
- f_{Det} : the relative detector sensitivity (ecc) [1]
- $f_{E,\alpha}$: the angle and energy dependent response, [1]
- H_{True} : the true dose [μSv]
- f_{Bg} : the response for background radiation, [1]
- h_{Bg} : the background dose [μSv]
- z : the blank signal [counts]

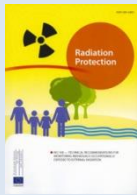


The measurement model

$$x = f_R f_{\text{Det}} (f_{E,\alpha} H_{\text{True}} + f_{\text{Bg}} h_{\text{Bg}}) + z$$

Diagram illustrating the measurement model equation with arrows pointing from terms to their definitions:

$$\text{signal} = \frac{\text{ref}_{\text{Cs},0}}{\text{dose}} \frac{\text{custom}}{\text{ref}_{\text{Cs},0}} \left\{ \frac{\text{ref}_{E,\alpha}}{\text{ref}_{\text{Cs},0}} \text{dose} + \frac{\text{ref}_{E_{\text{Bg}},0}}{\text{ref}_{\text{Cs},0}} \text{dose} \right\} + \text{signal}$$



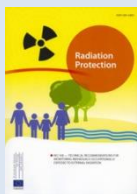
Components of a measurement model

Solving for an unknown dose

$$y = \frac{x - z}{f_R f_{\text{Det}} f_{E,\alpha}} - \frac{f_{\text{Bg}}}{f_{E,\alpha}} h_{\text{Bg}}$$

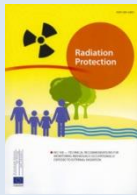
or using correction coefficients $k_i = \frac{1}{f_i}$

$$y = k_R k_{\text{Det}} k_{E,\alpha} (x - z) - \frac{k_{\text{Bg}}}{k_{E,\alpha}} h_{\text{Bg}}$$



Assigning distributions

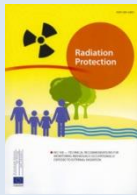
	Type	Distribution
x	A	normal
f_R, k_R	A	normal
f_{Det}, k_{Det}	B	normal
$f_{E,\alpha}, k_{E,\alpha}$	B	normal
f_{Bg}, k_{Bg}	B	normal
h_{Bg}	A	normal
z	A	normal



Uncertainty in measurement

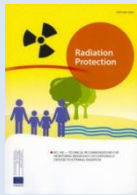
Think of all input quantities and the measurand as being a sample from a probability distribution

Doing measurements is obtaining random numbers from a distribution



Second stage

The calculation stage An example



Evaluating uncertainty

$$y = k_R k_{Det} k_{E,\alpha} (x - z) - \frac{k_{E,\alpha}}{k_{Bg}} h_{Bg}$$

$$C_{k_R} = k_{Det} k_{E,\alpha} (x - z)$$

$$C_{k_{Det}} = k_R k_{E,\alpha} (x - z)$$

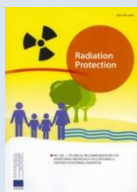
$$C_{k_{E,\alpha}} = k_R k_{Det} (x - z) - \frac{1}{k_{Bg}} h_{Bg}$$

$$C_x = k_R k_{Det} k_{E,\alpha}$$

$$C_z = -k_R k_{Det} k_{E,\alpha}$$

$$C_{k_{Bg}} = -\frac{k_{E,\alpha}}{k_{Bg}^2} h_{Bg}$$

$$C_{h_{Bg}} = \frac{k_{E,\alpha}}{k_{Bg}}$$



Evaluating uncertainty



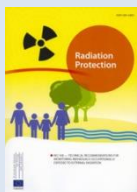
LiF:Mg,Ti + 1mm Al

	0	20	40	60
17.4	0.63	0.55	0.44	0.20
17.4	0.61	0.53	0.43	0.22
17.4	0.62	0.52	0.51	0.30
23.1	1.15	1.09	1.00	0.76
23.1	1.09	1.10	0.97	0.75
23.1	1.11	1.02	0.75	0.94
25.2	1.31	1.18	1.12	0.89
25.2	1.20	1.36	1.16	0.89
25.2	1.18	1.21	1.12	0.91
30.9	1.34	1.31	1.36	1.21
30.9	1.32	1.38	1.43	1.27
30.9	1.32	1.35	1.29	1.19
33	1.35	1.37	1.33	1.40
33	1.36	1.32	1.37	1.40
33	1.45	1.39	1.42	1.43
48	1.36	1.37	1.43	1.38
48	1.39	1.39	1.48	1.49
48	1.40	1.38	1.43	1.47
65	1.23	1.26	1.35	1.37
65	1.27	1.26	1.27	1.32
65	1.39	1.26	1.34	1.39
83	1.28	1.19	1.23	1.29
83	1.31	1.23	1.29	1.29
83	1.24	1.25	1.25	1.23
100	1.21	1.18	1.16	1.23
100	1.17	1.13	1.22	1.25
100	1.18	1.20	1.19	1.23
118	1.17	1.16	1.17	1.26
118	1.21	1.17	1.21	1.22
118	1.16	1.14	1.18	1.20
161	1.08	1.18	1.13	1.18
161	1.16	1.16	1.16	1.20
161	1.15	1.13	1.16	1.15
205	1.07	1.17	1.13	1.16
205	1.12	1.12	1.13	1.17
205	1.13	1.14	1.14	1.17
248	1.16	1.12	1.08	1.25
248	1.13	1.09	1.04	1.16
248	1.13	1.15	1.14	1.18
662	1.16	1.11	1.09	1.07
662	1.03	1.09	1.12	1.09
662	1.11	1.10	1.10	1.12
1250	0.98	0.99	1.03	1.01
1250	1.02	1.03	1.00	1.01
1250	1.00	0.98	0.98	1.03

Data triplet

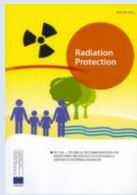
Energy keV	Angle 0	20	40	60
161	1.08	1.18	1.13	1.18
161	1.16	1.16	1.16	1.20
161	1.15	1.13	1.16	1.15
205	1.07	1.17	1.13	1.16
205	1.12	1.12	1.13	1.17
205	1.13	1.14	1.14	1.17
248	1.16	1.12	1.08	1.25
248	1.13	1.09	1.04	1.16
248	1.13	1.15	1.14	1.18
662	1.16	1.11	1.09	1.07
662	1.03	1.09	1.12	1.09
662	1.11	1.10	1.10	1.12

15 photon energies,
4 angles of incidence
In triplicate (180 data)



Numerical values

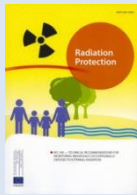
	expept.	range	u_i
x	1065 100	—	10 651
k_R	$10^{-3} \mu\text{Sv}$	—	$0.05 10^{-3}$
k_{Det}	1.00	0.85 — 1.15	0.05
$k_{E,\alpha}$	1.00	0.55 — 1.45	0.15
k_{Bg}	1.00	0.85 — 1.15	0.05
h_{Bg}	$65 \mu\text{Sv}$	—	6.5
z	100	—	5



Homework:

Use the equations in earlier sheets to calculate the

1. Dose
2. Standard uncertainty
3. Approximate 95% coverage interval



Now forget the

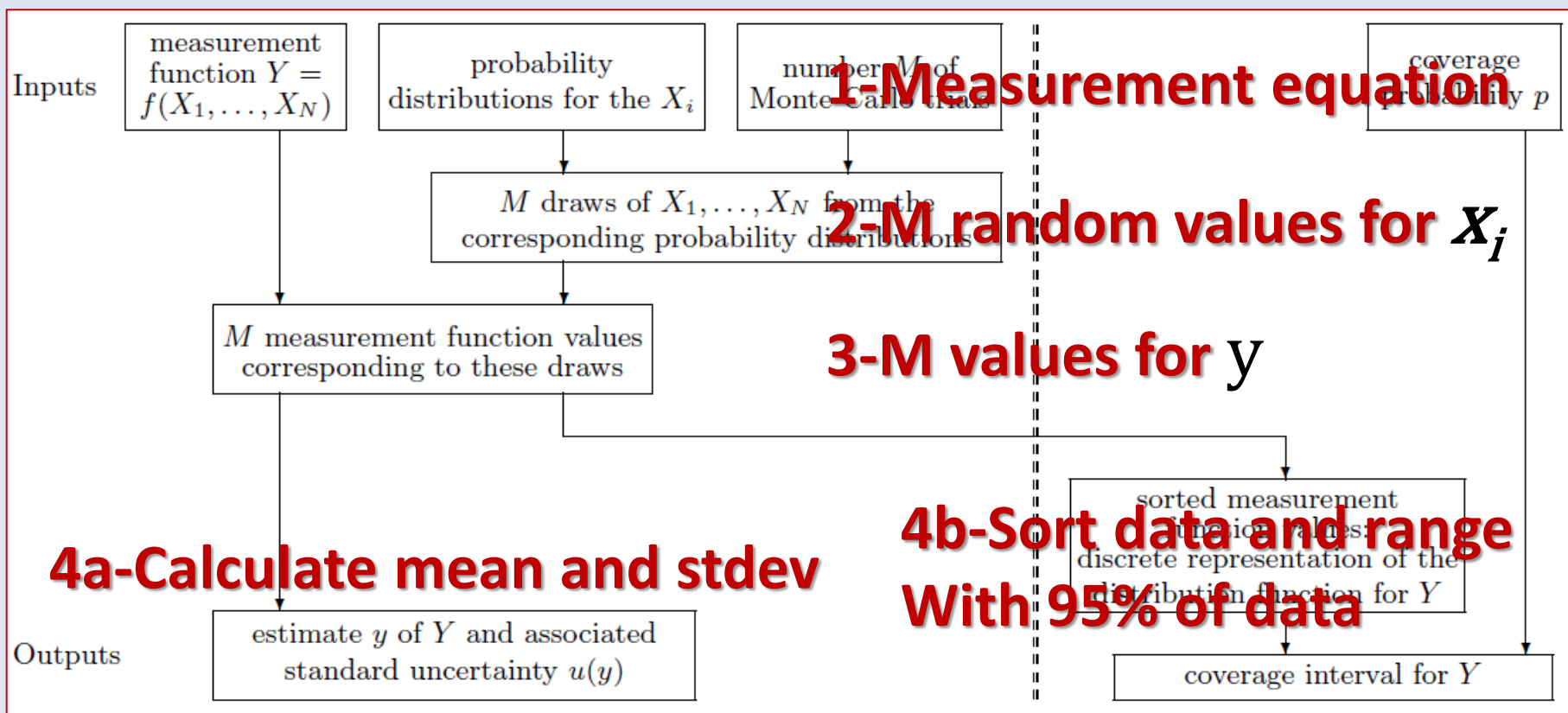
- LPU
- CLT
- Partial derivatives
- Welch-Satterthwaite
- Coverage factor

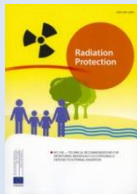
Solve

$$g_y(\eta) = \int \cdots \int_{-\infty}^{\infty} g_{\mathbf{X}}(\boldsymbol{\xi}) \delta(\eta - f(\boldsymbol{\xi})) d\xi_N \cdots d\xi_1$$

By Monte Carlo integration

Stage 2.1b The Monte Carlo method





A 23 line Python program doing complete MCM

```
import numpy.random as random
from scipy import stats as stats
#Define variables
M = 1000000 # number of Monte Carlo samples
X = {'x': 1065100, 'k_R': 1e-3, 'k_Det': 1.0, 'k_Ea': 1.0,
     'k_Bg': 1.0, 'h_Bg': 65.0, 'z': 100.0}
UX = {'x': X['x'] * 0.01, 'k_R': X['k_R'] * 0.05, 'k_Det': 0.05,
      'k_Ea': 0.15, 'k_Bg': 0.05, 'h_Bg': 6.5, 'z': 5.0}
#Generate M random numbers for input quantities
Xr = {} # will contain the random values for X
for k in X:
    Xr[k] = random.normal(X[k], UX[k], M)
#calculate M values for measurand
y = Xr['k_R'] * Xr['k_Det'] * Xr['k_Ea'] * (Xr['x'] - Xr['z']) - \
    Xr['h_Bg'] * Xr['k_Ea'] / Xr['k_Bg']
```

```
y.sort()
mean = y.mean()
stdev = y.std()
skew = stats.skew(y)
print('Mean:   %.2f' % mean)
print('Stdev:  %.3f' % stdev)
print('Skew:   %.3f' % skew)
print('Coverage: %.2f - %.2f' % (y[p], y[M-p]))
```

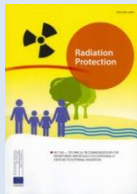
Output:

Mean: 999.71

Stdev: 168.56

Skew: 0.176

Coverage: 683.34 - 1345.33



Stage 2.1b The Monte Carlo method

On the practicum:

Doing MCM with a spread-sheet

Decision and detection thresholds