

Toolbox Measurement & Regulation

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General description

The objective of this toolbox is for students to understand and evaluate or implement a measurement-control chain, from the sensor to the control loops and the measurement statistics.

- UP1 : Measurement
- UP2 : Regulation

Pedagogy

Short courses (maxi 1h) , Practical works (Excel, Matlab, Simulink), Tutorials

Keywords

Measurement, regulation, automatic, uncertainties, calibration

Evaluation: examination (2x1.5h, 05/29/2018) with PC, authorized documents, evaluated program fixed 1 week before.

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Toolbox « **Measurement & Regulation** » 2018

13/3 & 27/3: Course + tutorials (Excel), Stats of measurement

3/4, 10/4 & 17/4: Course + tutorial (Excel, matlab, Simulink) „Rgulation“

13/4 (day): **Measurement & Regulation**, industry vision (N Caillet, Total)

15/5: Course + Tutorial „Advanced regulation“

18/5 (day): Course „Multivariate Analysis“+ tutorials (Matlab)

22/5: Course + industrial instrumentation problem solving « Sensors»

16/5: examination **regulation** et **measurement** (2 x 1h30, with PC)

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Statistics of the Measurement

- **Measurement** *Mesure*
- **Uncertainty** *incertitude*
- **Calibration** *Etalonnage*

Philippe Breuil, March, 2018

Metrology = science of the measurement

Physical and mathematical aspect

- **Statistics of the measurement:**
 - -Calculation of the uncertainties
 - -Calibration
- **Ways of measure: sensors**

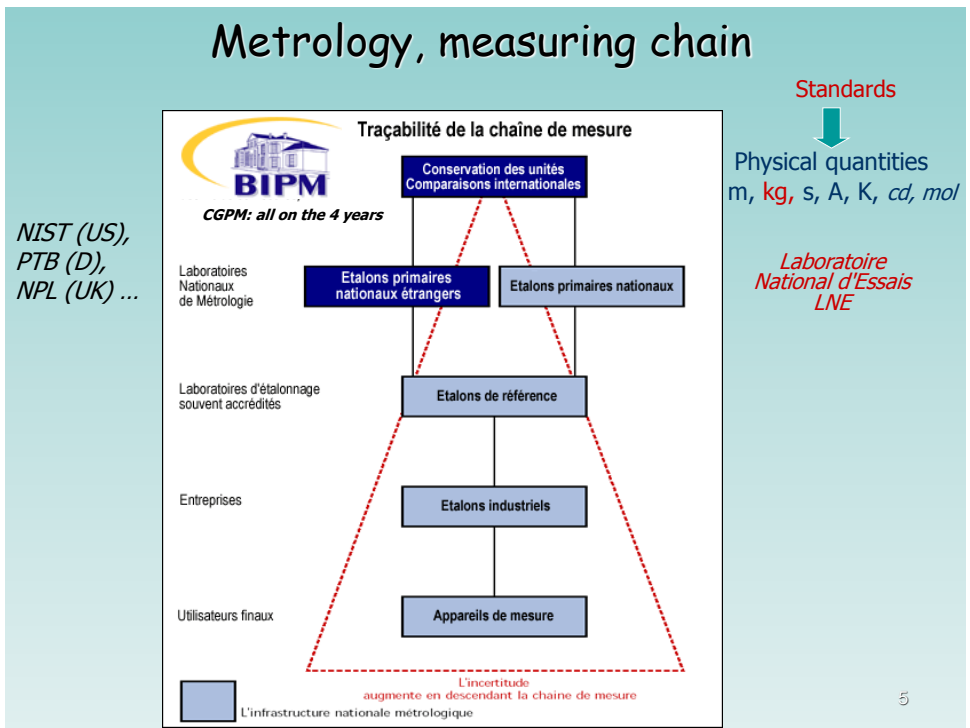
Legal aspect

- **Obligations during a commercial transaction**
- **Obligations for the publication of a measurement**

Economic aspect

- **Traceability and reliability**
- **Optimization of the quality**

Metrology, measuring chain



error and uncertainty ...

Measurement x of a variable of real value x_R : $x_R = E(x)$
(expectancy of x)
Espérance

Error: variable $\varepsilon = x_R - x$ $x = x_R + \varepsilon_B + \varepsilon_A$

- Systematic error: ε_B
Erreur Systématique
- Accidental or random error: ε_A
Erreur accidentelle ou aléatoire

Ni juste ni fidèle ("imprécis") Pas juste mais fidèle

Juste mais pas fidèle Juste et fidèle ("précis")

JUSTESSE ET REPETABILITE : EXEMPLE DE LA CIBLE

Systematic or random error?

- By definition, the random error is unpredictable (and thus not corrigible) and of null average value
- The systematic or random character of the error can depend on the context ...

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Systematic or random error?

- Ex: measure of a mass by means of a digital balance:

$$\text{Erreur: } \varepsilon = \varepsilon_a + \varepsilon_T + \varepsilon_o + \varepsilon_u + \varepsilon_s$$

ε_a : random error explained no
 ε_T : drift in temperature
 ε_o : error "operator"
 ε_u : error appropriate to the device
 ε_s : systematic Error of the series (!)

Conditions of the experiences:	ε_a	ε_T	ε_o	ε_u	ε_s
1 operator the same day, 1 device	Light Blue	Dark Blue	Dark Blue	Dark Blue	Dark Blue
Idem + spread over several days	Light Blue	Light Blue	Dark Blue	Dark Blue	Dark Blue
Idem + several operators	Light Blue	Light Blue	Light Blue	Dark Blue	Dark Blue
Idem + tests on a set of devices	Light Blue	Light Blue	Light Blue	Light Blue	Dark Blue

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Characterization of the measurement (and of the random error):

- Estimated mean of n measures of the same value x_R

Moyenne estimée

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\lim_{n \rightarrow \infty} (\bar{x}) = x_R = E(x)$$

$n \rightarrow \infty$

$x_R = \text{real value}$

(Expectation of x)

Espérance

(Law of large numbers)

Loi des grands nombres

(If random error only)

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Standard deviation of the random error:

Ecart-type de l'erreur aléatoire

Variance (of the random error): $V = E((x - E(x))^2) = \overline{(x - x_R)^2}$

Variance

Standard deviation of the random error $\sigma = \sqrt{V}$

error

$$\sigma = \sqrt{\overline{(x_i - E(x))^2}} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - E(x))^2}$$

Real value, A priori unknown ...

estimated Standard deviation of the random error

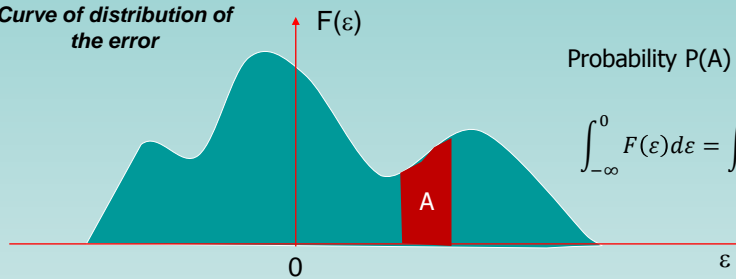
$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad E(s) = \sigma$$

Relative standard deviation: $\sigma_r = \frac{\sigma}{|x|}$

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Distributions of (random) errors

Curve of distribution of the error



$$\text{Probability } P(A) = \int_A F(\varepsilon) d\varepsilon$$

$$\int_{-\infty}^0 F(\varepsilon) d\varepsilon = \int_0^{+\infty} F(\varepsilon) d\varepsilon = 0.5$$

- Gaussian or normal *
 - Uniform,
 - Poissonian,
 - Etc. ...
- *Gaussian gold normal **
 - *Uniform,*
 - *Poissonian,*

* The most prevalent, thanks to the limit central Theorem ...

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Central theorem limits

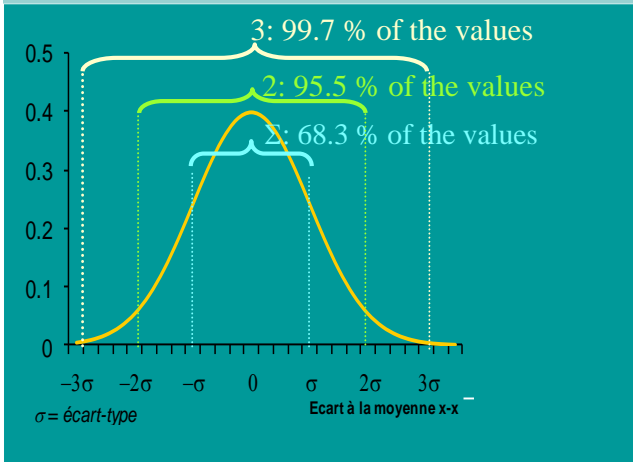
Limit Theorem exchange

- If a variable is the resultant of a large number of causes, small, with additive effect, this variable aims towards a ***normal law***.
- It is because of this interpretation that the normal law is very often used as model (unfortunately not always adequately).

[Demo](#)

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The Gaussian distribution (or normal)



$$F(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\bar{x}}{\sigma}\right)^2}$$

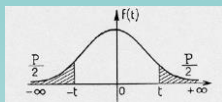
P	Width t
50 %	0,67·σ
68 %	1·σ
70 %	1,04·σ
87 %	1,5·σ
90 %	1,65·σ
95 %	1,96·σ
99 %	2,56·σ
99,7 %	3·σ
99,9 %	3,28·σ
99,999 999 8 %	6·σ

$$P = \text{proba} \left[|X - X_R| < t \cdot \sigma \right]$$

Valid only if standard deviation calculated "comfortably" ($n > 20$)

Otherwise, Gauss → Student... 14

The coefficient t of Student



		Student coefs. t				
conf. Interv.		90.0%	95.0%	98.0%	99.0%	99.9%
p		0.1	0.05	0.02	0.01	0.001
N=nb deg lib						
1		6.31	12.71	31.82	63.66	636.62
2		2.92	4.30	6.96	9.92	31.60
3		2.35	3.18	4.54	5.84	12.92
4		2.13	2.78	3.75	4.60	8.61
5		2.02	2.57	3.36	4.03	6.87
6		1.94	2.45	3.14	3.71	5.96
7		1.89	2.36	3.00	3.50	5.41
8		1.86	2.31	2.90	3.36	5.04
9		1.83	2.26	2.82	3.25	4.78
10		1.81	2.23	2.76	3.17	4.59
12		1.78	2.18	2.68	3.05	4.32
14		1.76	2.14	2.62	2.98	4.14
17		1.74	2.11	2.57	2.90	3.97
20		1.72	2.09	2.53	2.85	3.85
30		1.70	2.04	2.46	2.75	3.65
40		1.68	2.02	2.42	2.70	3.55
50		1.68	2.01	2.40	2.68	3.50
100		1.66	1.98	2.36	2.63	3.39
100000		1.64	1.96	2.33	2.58	3.29

N = Nb samples used for the calculation of -1
= Nb of degrees of freedom

Reminder: valid only for gaussian law!

Relation standard deviation / Gaussian:
 valid only if standard deviation perfectly known ($n = \infty$)

Practically, st. Dev. Determined from a statistical calculation:

-> Student's law

(tends to gaussian if n big, $n > 20$)

$$P = \text{proba} \left[|X - X_R| < t \cdot \sigma \right]$$

$$P = \text{TDIST}(t; N; 2)$$

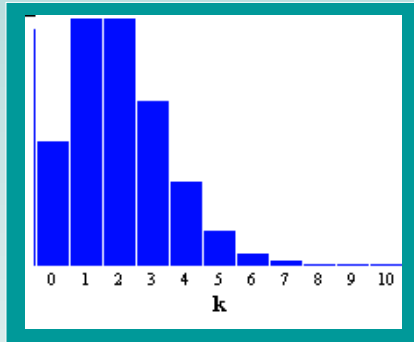


$$t = \text{LOI.STUDENT.INVERSE.BILATERALE}(P, N)$$



Distribution of Poisson

- Ex: counting of not simultaneous events (radioactive decomposition, queue...)



$$P(r) = \frac{\mu^r e^{-\mu}}{r!}$$

Mean: μ

Variance: μ

[Demo](#)

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The Significance tests in measurement

Tests d'hypothèse

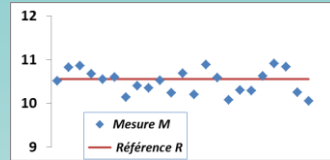
Tests of a hypothesis (" null hypothesis ", ex: 2 samples have the same mean)) from a finite number of measurements, with random error. The result of the test is not absolute but is a probability which is a help to the validation or not of the initial hypothesis, **thus it never establishes a proof.**

Parametric tests (Hypothesis on distribution + or - necessary)	
1-sample T-test	Comp. Sample with reference value, confidence interval
2-samples T-test	Comparison of 2 samples
F-test	Comparison of the variance of 2 samples
ANOVA	Variance analysis: analysis of the variances of K samples, comparison of the means
Test Chi-public garden	Use in particular to verify a hypothesis of distribution
Grubbs ' test	Detection of the absurd values ("outliers")
Non parametric Tests (No hypothesis on distribution)	
Test Wilcoxon. Mr. W	Comparison of 2 samples, method of row

In red: described tests + far, otherwise to see biblio or google

"simplified" one-sample T-test

Comparison of the measurement M of a sample with a reference value R , it is assumed that the distribution is normal.

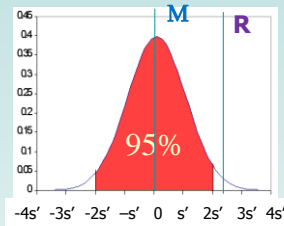


Hypothesis:

- « is M est different from R »? **Yes, almost always, because of the random error ...**
- « Is M significantly different from R »?
- « The difference between M and R is "probably" not only due to random error. »

This H1 difference hypothesis is used if its probability is greater than 95% (for example) (or if the probability of equality is less than 5% (H2))

1 measurement: M , standard deviation: s , Gaussian distr.



Hypothesis retained if:

$$|M - R| \geq t \cdot s \quad (t = \text{Student's coef.})$$

if s can be calculated « accurately »:

	H1: 95% (or H2: 5%)	H1: 99% (or H2: 1%)	H1: 99.9% (or H2: 0.1%)
t	1.96	2.56	3.28

**n > 20, otherwise, Student's coefs table...*

« official » one-sample T-test

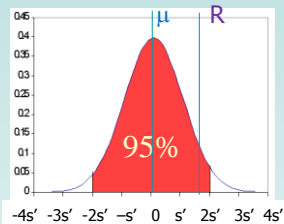
Comparison of the μ average of a sample with a reference value R , it is assumed that the distribution is normal*.

Hypothesis: « the difference between the mean of n measurements and a reference value is not due solely to random errors »

This hypothesis is retained if its probability is greater than 95% (for example)

n measurements: mean μ , estimated standard deviation: s

The estimated standard deviation **of the mean** is shown (down...) to be: $s' = \frac{s}{\sqrt{n}}$



Hypothesis retained if:

$$|\mu - R| \geq t \frac{s}{\sqrt{n}} \quad (t = \text{Student's coef.})$$

if s can be calculated « accurately »:

	H1: 95% (or H2: 5%)	H1: 99% (or H2: 1%)	H1: 99.9% (or H2: 0.1%)
t	1.96	2.56	3.28

one-sample T-test, example

Hypothesis: "The difference between the mean of n weighing of a standard mass of 1 kg and the value of this mass **is not** due only to random errors".

There is a "bias"...

Probability > 95% hypothesis retained!

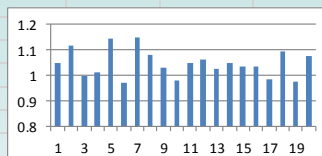
$$|\mu - R| \geq t \cdot \frac{s}{\sqrt{n}}$$

True!



$$t = \frac{|\mu - R|}{\frac{s}{\sqrt{n}}}$$

1	1.04946993			
2	1.11917309	Standard R (!)	1.0000	
3	0.99865798			
4	1.01040713			
5	1.14655592			
6	0.97054733			
7	1.14894136			
8	1.08005111	mean μ :	1.04614199	
9	1.03044121	Standard dev	0.05326172	
10	0.98202478			
11	1.05094267	$ \mu - R $	0.0461	
12	1.06252219			
13	1.02608401	$t \cdot \frac{s}{\sqrt{n}}$	0.02381937	(t=2)
14	1.04961426			(n=20)
15	1.03483134			
16	1.03475702			
17	0.98306671			
18	1.09287381			
19	0.97490694			
20	1.07697103			



two-sample T-test

Comparison of 2 means of 2 samples, it is assumed that the distribution is normal.

Hypothesis: "The **difference** between the two **means is not** just due to random errors."

This assumption is used if its probability is greater than 95% (for example)

	Samp 1	Samp 2
Nb meas.	n_1	n_2
Est. Std. Dev.	s_1	s_2
Est. mean	μ_1	μ_2

Comparison of μ_1 and μ_2 :

Can be reduced to a 1-sample-test by comparing $|\mu_1 - \mu_2|$ to 0

We use then as standard deviation of $|\mu_1 - \mu_2|$:

$$s = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}} \quad (\text{demonstrated in part "error propagation laws"})$$

$$\text{Hypothesis retained if: } |\mu_1 - \mu_2| \geq t \cdot s \quad |\mu_1 - \mu_2| \geq t \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

And the number of degrees of freedom* is a first approximation: $n_1 + n_2 - 2$

$$(\text{otherwise: } df = \frac{\left[\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right]^2}{\frac{(s_1^2/n_1)^2}{n_1-1} + \frac{(s_2^2/n_2)^2}{n_2-1}})!$$

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* Number of degrees of freedom (DOF)

The number of degrees of freedom is the number of **independent** observations in a sample of data that are available to estimate a parameter of the population from which the sample is drawn.

- Ex, n random variables: X_1, \dots, X_n
- Mean of the sample: $\bar{X}_n = \frac{X_1 + \dots + X_n}{n}$
- « Residuals » (« errors $X_i - \mu$ »): $X_i - \bar{X}_n \quad \sum = 0$

If n-1 known residuals, we can know the last one..., so n-1 DOF! So for the calculation of the « residual » parameter, the number of DOF is n-1, same for standard deviation.

We must have $DOF > 0$, so if n-i DOF, $n=i+1$ will be the minimum size for estimating the parameter.

Ex: calculation of a standard deviation: possible from $n=2$, no sense if $n=1$

[https://en.wikipedia.org/wiki/Degrees_of_freedom_\(statistics\)](https://en.wikipedia.org/wiki/Degrees_of_freedom_(statistics))

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two-sample T-test: example

Hypothesis: "The difference between the averages of weighing of the same mass per 2 operators is not due only to random errors".

There is a "bias between the 2 operators"...



Probability < 95%! hypothesis rejected!

$$|\mu_1 - \mu_2| \geq t \cdot \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

False!



op1	op2		op1	op2
3.59385514	3.49673556	mean μ	3.54463973	3.55551443
3.58810682	3.50481358	std. Dev. s	0.04510027	0.04809217
3.53371004	3.47201328			
3.52760094	3.553306	$ \mu_1 - \mu_2 $		0.0108747
3.44867115	3.57512954			
3.51024893	3.55717682			
3.60880932	3.62969549	$s = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$		0.0139361
3.53927667	3.66487781	n:	43	t=2
3.55719746	3.54702026			
3.52552333	3.54598904	s.t:	0.02787228	
3.49798625	3.48741103			
3.49706929	3.56409401			
3.56771949	3.56622487			

Sample	op1	op2
1	3.58384532	3.50903522
2		
3		
4		
5		
6		
7		
8		
9		
10		
11		
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Confidence interval

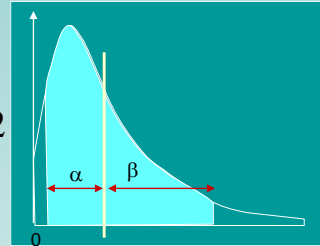
Intervalle de confiance

The confidence interval at p (95%) of an x -measurement is an interval of values that has a centered probability p (95%) of containing the true x_R value of the estimated parameter.

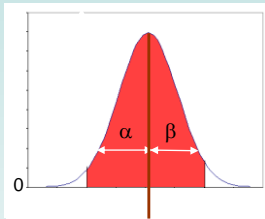
$$[x - \alpha, x + \beta]$$

$$P(x_R < x - \alpha) = P(x_R > x + \beta) = (1 - p) / 2$$

α et β = uncertainty at p (95%)



The calculation of α and β as a function of probability P (usually 95%) depends on the distribution law of the error.



Symmetric distribution:

- $\alpha = \beta$
- Mean value of the measurement = the more probable



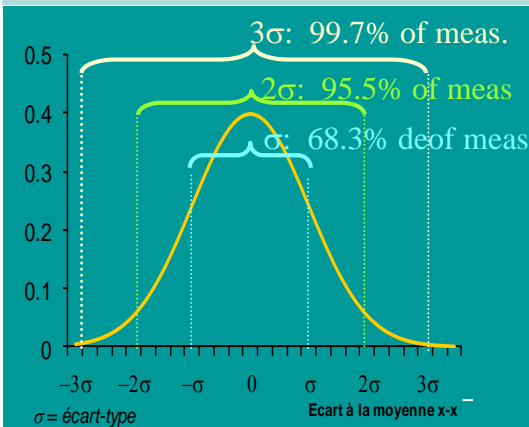
Normal distribution

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Confidence interval, case of normal distribution:

The confidence interval at p (95%) of an x -measurement x is an interval of values that has a probability centered p (95%) of containing the true x_R value of the estimated parameter.

$$[x - t.s, x + t.s]$$



Number of values - 1 for the calculation of σ

		Student's coefs t				
conf. interval	p	90.0%	95.0%	98.0%	99.0%	99.9%
		0.1	0.05	0.02	0.01	0.001
	deg freedom					
	1	6.31	12.71	31.82	63.66	636.62
	2	2.92	4.30	6.96	9.92	31.60
	3	2.35	3.18	4.54	5.84	12.92
	4	2.13	2.78	3.75	4.60	8.61
	5	2.02	2.57	3.36	4.03	6.87
	6	1.94	2.45	3.14	3.71	5.96
	7	1.89	2.36	3.00	3.50	5.41
	8	1.86	2.31	2.90	3.36	5.04
	9	1.83	2.26	2.82	3.25	4.78
	10	1.81	2.23	2.76	3.17	4.59
	12	1.78	2.18	2.68	3.05	4.32
	14	1.76	2.14	2.62	2.98	4.14
	17	1.74	2.11	2.57	2.90	3.97
	20	1.72	2.09	2.53	2.85	3.85
	30	1.70	2.04	2.46	2.75	3.65
	40	1.68	2.02	2.42	2.70	3.55
	50	1.68	2.01	2.40	2.68	3.50
	100	1.66	1.98	2.36	2.63	3.39
	100000	1.64	1.96	2.33	2.58	3.29

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Writing a measurement (normal distribution)


The result of a measurement must have 4 elements:
Ex : $C_{NO} = 125.3 \text{ ppb} \pm 1.7 \text{ ppb}$ (à 95% ou $k=2$)

- 1 : Numerical value with a correct number of decimals
- 2 : Unit
- 3 : expanded uncertainty = t.s
- 4 : Coverage factor t


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Evaluation of uncertainty* :

 **Evaluation by statistical analysis of series of measurements ("Type A")**
(usually measurement, but also simulation)

 **Calculation evaluation of the effect on the final uncertainty of the different sources of uncertainty ("Type B": "by any other means!"), themselves evaluated:**

With a « type A » method,
by manufacturer data, calibration etc...

It is then necessary to know the laws of propagation of uncertainty... 

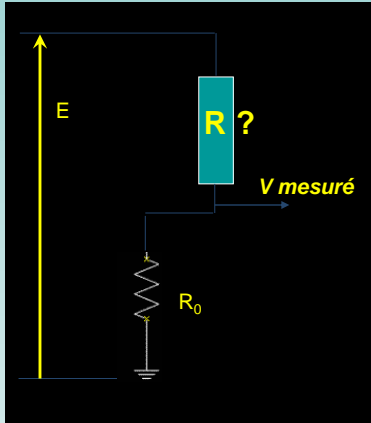
***GUM : Guide to the expression of Uncertainty in Measurement (1993)**

Norme Française X 07-020 AFNOR Août 1999

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Evaluation by statistical analysis of series of measurements

Example: Evaluation of resistance measurement:



$$V = E \frac{R_0}{R + R_0} \quad \longrightarrow \quad R = R_0 \frac{E - V}{V}$$

Measurement and calculation with a large number of N "standard" resistors (R known)

Calculation of standard deviation σ

95% uncertainty = $t \cdot \sigma$, # 2σ if $N > 15$

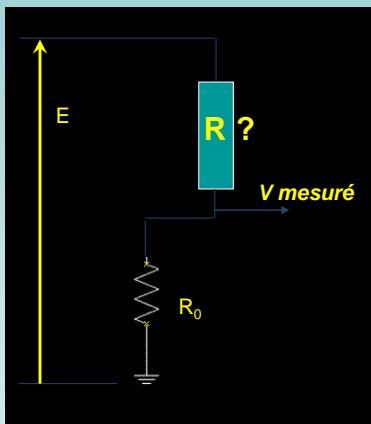
Ignoring:

- The uncertainty of the Vmeter,
- Uncertainties about E, R_0 , standard resistors...

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Calculation-based assessment of the effect on the final uncertainty of the different sources of uncertainty

Example: measurement of a resistor:



$$R = R_0 \frac{E - V}{V}$$

$\sigma(R_0)$, $\sigma(E)$, $\sigma(V)$ known

combined standard uncertainty

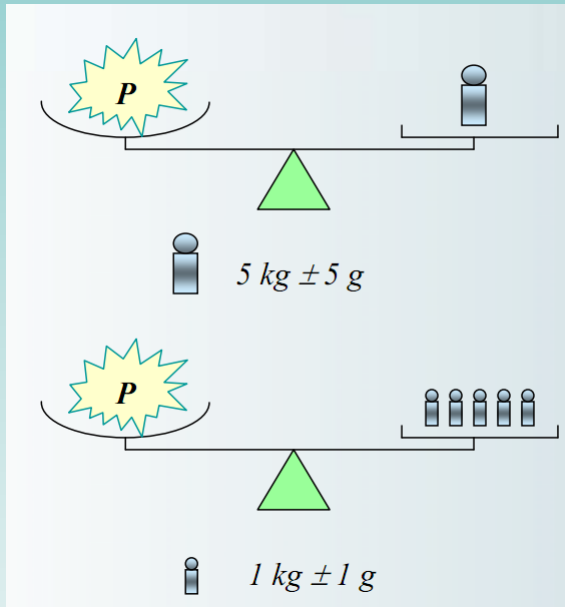
Loi de propagation des écart-types

$$\sigma(R) = \sqrt{\left(\frac{E - U}{U} \sigma(R_0)\right)^2 + \left(\frac{R_0}{V} \sigma(E)\right)^2 + \left(\frac{R_0 E}{V^2} \sigma(V)\right)^2}$$

explanation \Rightarrow

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What is the most accurate weighing?

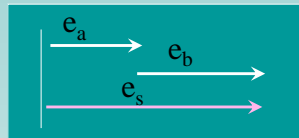


combined standard uncertainty for random & independent errors (1)

Example of the sum: $s = a + b$

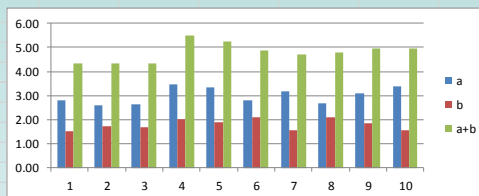
Reminder: errors are added algebraically:

$$e_s = e_a + e_b$$



And Standard deviations?

	a	b	a+b
	2.82	1.51	4.33
	2.61	1.71	4.32
	2.64	1.68	4.32
	3.45	2.02	5.48
	3.32	1.90	5.23
	2.79	2.08	4.88
	3.17	1.55	4.72
	2.70	2.09	4.79
	3.10	1.86	4.96
	3.40	1.56	4.95
mean	3.00	1.80	4.80
variance	0.11	0.05	0.16
Std. Dev.	0.33	0.23	0.39



4.80 sum of means
0.16 sum of variances
0.55 sum of standard deviations

combined standard uncertainty for random & independent errors (2)

Example of the sum: $s=a+b$

Random error:

$$\sigma(s) \leq \sigma(a) + \sigma(b)$$

Standard deviations are not added!!

$$\text{Var}(a+b) = \text{Var}(a) + \text{Var}(b) \quad \text{Variances do!!}^*$$



$$(\sigma(a+b))^2 = \sigma(a)^2 + \sigma(b)^2 \quad \rightarrow \quad \sigma(a+b) = \sqrt{\sigma(a)^2 + \sigma(b)^2}$$

Standard deviations are added quadratically*

** If the errors are independent and random*

Addition of variances, demonstration:

Example of the sum: $s=a+b$

$$\text{Variance: } \text{Var}(a) = \frac{1}{n-1} \sum (a_i - \bar{a})^2 \quad \text{Var}(b) = \frac{1}{n-1} \sum (b_i - \bar{b})^2$$

$$\text{Var}(s) = \frac{1}{n-1} \sum (a_i - \bar{a} + b_i - \bar{b})^2 = \frac{1}{n-1} \left(\sum (a_i - \bar{a})^2 + \sum (b_i - \bar{b})^2 + 2 \sum ((a_i - \bar{a})(b_i - \bar{b})) \right)$$

$$\text{Var}(a+b) = \text{Var}(a) + \text{Var}(b) + 2\text{Cov}(a,b)$$

=0 if independent errors

Variances can be added,



And for standard deviations?

$$\sigma(a+b) = \sqrt{\sigma(a)^2 + \sigma(b)^2}$$

Quadratic sum of standard deviations

Uncertainties: si $I = t \cdot \sigma$, $I(a+b) = \sqrt{I(a)^2 + I(b)^2}$
(if same distributions...)

What is the most accurate weighing?

⇒ Result of measurement :

$$P = 5 \text{ kg} \pm 5 \text{ g}$$

⇒ Result of measurement :

$$P = P_1 + P_2 + P_3 + P_4 + P_5$$

$$c_{i=1\dots 5} = 1$$

$$s(P) = \sqrt{\sum_{i=1}^5 s(P_i)^2} = \sqrt{5 \cdot (0.5)^2} = 1.12 \text{ g}$$

$$P = 5 \text{ kg} \pm 2.24 \text{ g}$$

combined standard uncertainty for random & independent errors (3)

Fundamental application in instrumentation: **The mean**

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad \longrightarrow \quad \sigma(\bar{x}) = \frac{1}{n} \sqrt{\sum_{i=1}^n \sigma(x)^2} = \frac{\sigma(x)}{\sqrt{n}}$$

Theorem of the mean

If a series of measurements has a random and independent standard deviation s error, then the mean of n of these measurements has a random error whose standard deviation is divided by square root of n .

Reminder: law of propagation of a "small" error

$$y = f(x) \quad f(x + \Delta x) = f(x) + \frac{df}{dx} \cdot \Delta x$$

$$\Delta y = \frac{df}{dx} \cdot \Delta x$$

Any function: $y = f(x_1, \dots, x_i, \dots)$

error $\Delta(y) = \sum_1^n \left(\frac{\partial f}{\partial x_i} \right) \Delta x_i$

Special case: product-power, logarithmic derivative...

$$y = A \prod_i x_i^{\alpha_i} \quad \longrightarrow \quad \frac{\Delta(y)}{y} = \sum_i \left(\alpha_i \frac{\Delta(x_i)}{x_i} \right)$$

Relative error

NOT VALID FOR STANDARD DEVIATION!!

Law of propagation of variance and standard deviation

Any function: $y = f(x_1, \dots, x_i, \dots)$

$$\Delta(y) = \sum_1^n \left(\frac{\partial f}{\partial x_i} \right) \Delta x_i$$

The variance is additive, if the variables x_i are independent, "we show that":

$$V(y) = \sum_1^n \left(\frac{\partial f}{\partial x_i} \right)^2 V(x_i)$$

Std. Dev. : $V(\mathbf{x}) = (\sigma(\mathbf{x}))^2$ $\sigma^2(y) = \sum_1^n \left(\frac{\partial f}{\partial x_i} \right)^2 \sigma^2(x_i)$

General case (non-independent variables):

$$\sigma^2(y) = \sum_1^n \left(\frac{\partial f}{\partial x_i} \right)^2 \sigma^2(x_i) + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \frac{\partial f}{\partial x_i} \frac{\partial f}{\partial x_j} \text{Cov}(x_i, x_j) \quad \mathbf{!}$$

Uncertainty Propagation Laws (1)

Any function: $y = f(x_1, \dots, x_i, \dots)$

$$\sigma^2(y) = \sum_1^n \left(\frac{\partial f}{\partial x_i} \right)^2 \sigma^2(x_i)$$

Uncertainty for normal distr. : $I(y) = t \cdot \sigma(y)$, generally, $t \sim 2$

$$I^2(y) = \sum_1^n \left(\frac{\partial f}{\partial x_i} \right)^2 I^2(x_i)$$

If:

- **same coeffs t**
- **Independent variables x_i**

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Uncertainty Propagation Laws (1)

Products & powers :

Interesting property of relative standard deviations: $\frac{\sigma(x)}{x}$

$$y = A \prod_i x_i^{\alpha_i} \quad \longrightarrow \quad \left(\frac{\sigma(y)}{y} \right)^2 = \sum_i \left(\alpha_i \frac{\sigma(x_i)}{x_i} \right)^2$$

Quadratic sum of **relative** standard deviations

Example: $y = \frac{a \cdot b \cdot c^3}{d^{1/2}}$

$$\longrightarrow \frac{\sigma(y)}{y} = \sqrt{\left(\frac{\sigma(a)}{a} \right)^2 + \left(\frac{\sigma(b)}{b} \right)^2 + \left(3 \frac{\sigma(c)}{c} \right)^2 + \left(1/2 \frac{\sigma(d)}{d} \right)^2}$$

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Calculation of uncertainty by **simulation** of random error or Monte Carlo method



$$\text{Ex: } y=f(x_1,x_2),$$

x_1 and x_2 have random errors (not necessarily independent) characterized by their standard deviations s_1 and s_2

- Simulate a certain number of experiments with the same values x_1 and x_2 + random error (\neq drawings)

$$y_i=f(x_1+\varepsilon_1,x_2+\varepsilon_2)$$

N times

- The ε_i are calculated using a random number generator with adequate distribution (usually normal*)

- **Calculation of the standard deviation of the y_i**

*Excel: =NORMSINV(RAND());0;std dev)

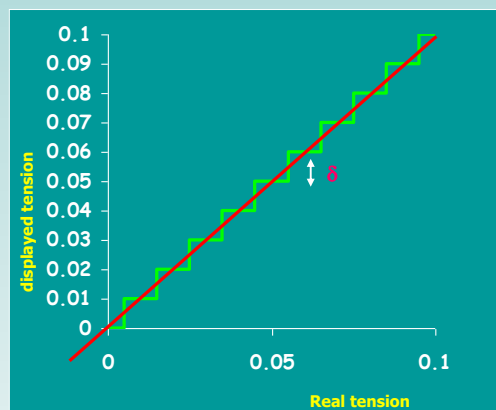
TP4

*Excel: =LOI.NORMALE.INVERSE(ALEA());0;écart-type)

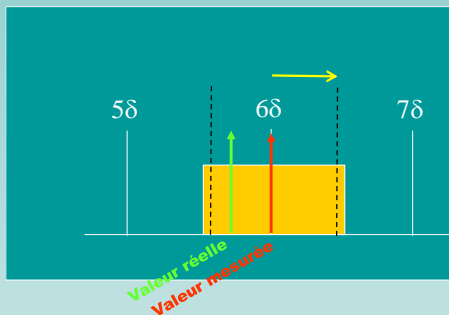
Discretization uncertainty

L'incertitude due à la discrétisation

- Discretization occurs when the final values constitute a discrete set.
- **Resolution** δ of the acquisition system, not to be confused with *uncertainty* or *sensitivity*.



Discretization uncertainty (2)



Maxi error: $\delta/2$

$$\sigma_d = \sqrt{\frac{1}{\delta} \int_{-\frac{\delta}{2}}^{\frac{\delta}{2}} x^2 dx} = \frac{\delta}{2\sqrt{3}} = 0.29\delta$$

Standard deviation of the error due to discretization:

$$\sigma_d = \frac{\delta}{2\sqrt{3}}$$

95% uncertainty due to discretization: $2\sigma_d$?

No! $I_d^{95\%} = 0.975 \frac{\delta}{2}$

0.58δ

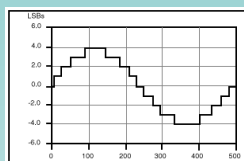
0.485δ

$$I_d^{95\%} \approx \frac{\delta}{2}$$

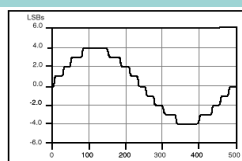
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The « Dithering »

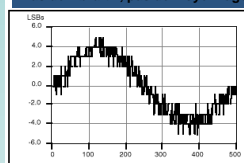
The averaging method can also reduce the discretization error (= quantization):



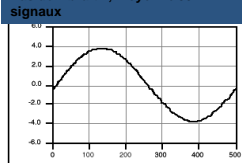
Pas de « bruit », pas de moyennage



Pas de « bruit », moyenne 50 signaux



« bruit », pas de moyennage



« bruit », moyenne 50 signaux

You can gain 1 resolution bit every time you multiply the sampling rate by 4...

... provided that the signal before digitizing contains a noise (random and independent) of RMS value higher than the initial resolution...

The presence of random error here allows to improve the "accuracy" of the measurement!!

[demo](#)

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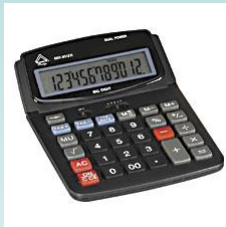
Discretization uncertainty : (3) significant decimal places

Writing a number with a finite number of digits → discretisation error

For a measurement, the standard deviation of the introduced error must be small compared to the standard deviation of the initial measurement error.

But digital systems can give a lot of significant numbers...

Ex: measure = 438.2659872 Std. Dev. measure = 0.55 (0.125 % in relatif)



438.2659872 ?

Must we write:

438.265 ?

438.3 ?

438?

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Discretization uncertainty : (4) significant decimal places, example

Ex: measure = 438.2659872 Std. Dev. measure = $\sigma(x) = 0.55$ (0.125 % in relatif)

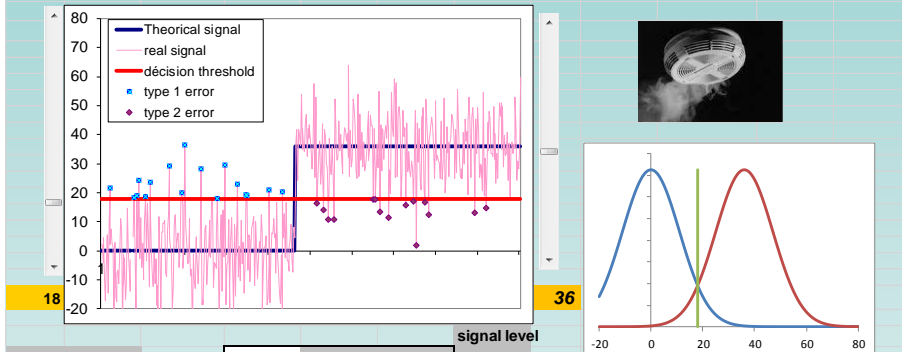
Displayed meas. <i>resolution</i>	S.D. discretisation error $I_d^{95\%} = 0.95 \frac{\delta}{2}$	S.D. final error $\sigma(X) = \sqrt{\sigma^2(x) + \sigma_d^2}$	% of error due to discretisation
438.265987 0.000001	2.4 10 ⁻⁷	0.55	< 10 ⁻³ %
438.27 0.01	2.4 10 ⁻³	0.550008	10 ⁻³ %
438.3 0.1	0.024	0.5506	0.14 %
438 1	0.24	0.62	13 %
440 10	2.4	2.94	434 %

- You can choose the resolution immediately smaller than the standard deviation of the measurement.
- The standard deviation (or uncertainty) displayed must not exceed 2 significant digits.

Limit of detection (LOD)

Detect = determine if measurement is zero or not

LOD = Smallest non-zero value detectable with a certain probability of error, equalizing the risk of false >0 and false <0



If normal distr. and probability dofe 95%:

$$\text{LOD} = 3.3\sigma$$

We often take: $\text{LOD} = 3\sigma$

σ = standard deviation of the "close to zero" measurement

Calibration of a measuring system

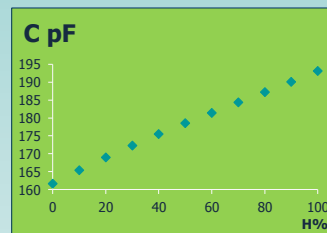
Calibration: "Operation consisting in establishing a relationship between the values of the quantity indicated by a measuring instrument and the corresponding values of the quantity produced by **standards**" (VIM)

measurement SPECIALTIES

HS1101LF – Relative Humidity Sensor



- Lead free component
- High reliability and long term stability
- Patented solid polymer structure
- Suitable for linear voltage or frequency output circuitry
- Fast response time and very low temperature coefficient



POLYNOMIAL RESPONSE OF HS1101LF

$$C \text{ (pF)} = C@55\% \cdot (3.903 \cdot 10^{-8} \cdot RH^3 - 8.294 \cdot 10^{-6} \cdot RH^2 + 2.188 \cdot 10^{-3} \cdot RH + 0.898)$$

REVERSE POLYNOMIAL RESPONSE OF HS1101LF

$$RH \text{ (\%)} = -3.4656 \cdot 10^{-13} \cdot X^3 + 1.0732 \cdot 10^{-4} \cdot X^2 - 1.0457 \cdot 10^{-4} \cdot X + 3.2459 \cdot 10^{-3}$$

With $X = C(\text{read}) / C@55\%RH$

Sensors & Instruments

« variables transformer »



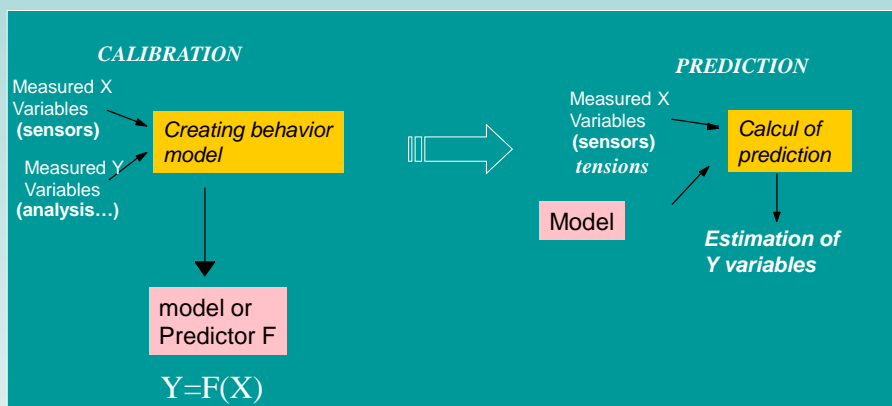
- Input ("Yvariables"):**
- System status variable
 - Difficult to measure
 - (ex: pressure...)

- Output ("Xvariables"):**
- Variable output from sensor
 - easy to measure
 - (e. g. electrical signal...)

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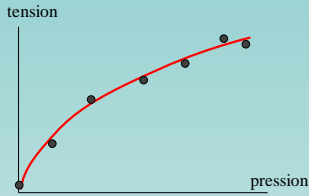
Calibration: Creation of a behavior model

Etalonnage: Création d'un modèle de comportement

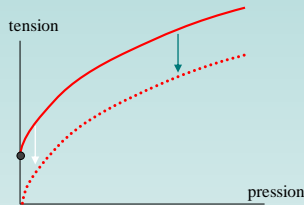


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Calibration - Gauging (zero adjustment)



- **Calibration (*Etalonnage*)** The complete calculation of the model requires a "large" number of experiments.



- **Gauging or zero adjustment (*calibrage*)** = The "realignment" of the model requires 1 experiment ("zero"), or even 2 ("zero + gain").
 - Correction of manufacturing variations
 - Drift correction
 - Correction of experimental conditions (temperature, balance calibration...)
 - Etc...

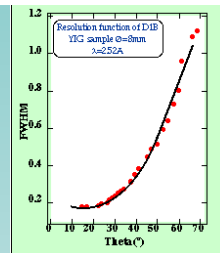
If the model is not linear, the zero adjustment can only correct small variations...

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The least Squares

Les moindres carrés

Least squares method (monovariate):



We want to model: $\hat{y}_i = f(x_i)$, in fact, based on experiments, we have: $y_i = f(x_i) + e_i$ where e_i = "residual" or error.

$$e_i = y_i - f(x_i) = y_i - f(x_i, \theta_1, \dots, \theta_j)$$

Minimal, for the set of calibration measurements, by finding the optimal function f with parameters $\theta_1, \dots, \theta_j$

θ_j represents the parameter(s) of the function to be optimized, f (ex: coefs polynôm)

We usually use the Euclidean distance:

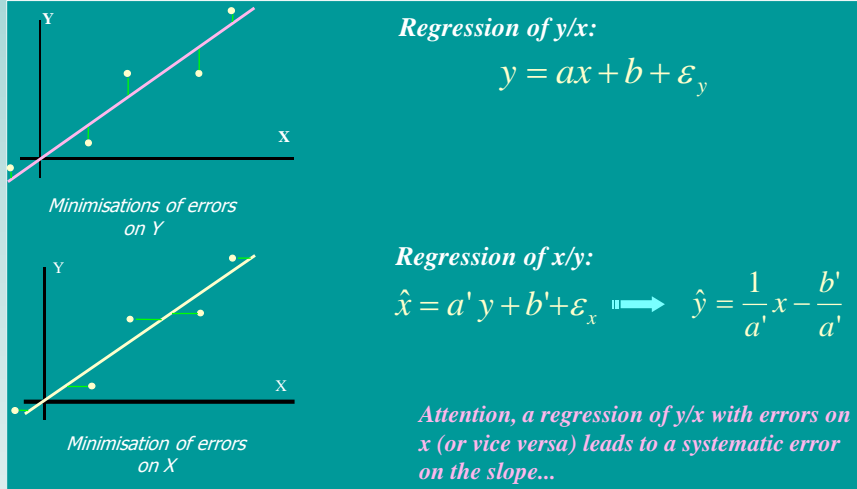
$$\sum_i (y_i - f(x_i, \theta_1, \dots, \theta_j))^2 \quad \text{« minimale »}$$

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Linear regression

La régression linéaire

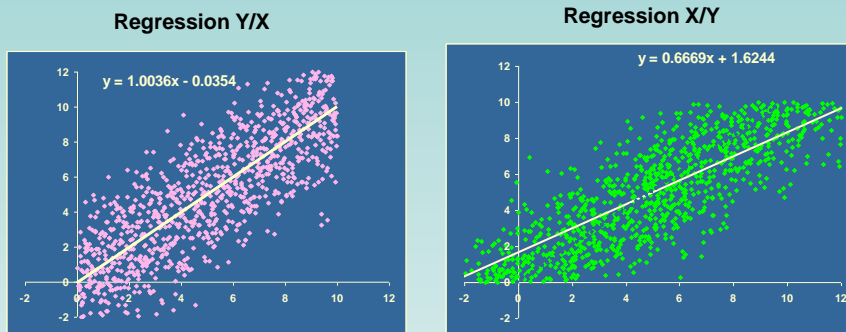
- Monovariate ($y=f(x)$) + linear hypothesis ($y=ax+b$)
- 2 cases:



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Linear regression: y/x ou x/y ?

Attention, a regression of y/x with errors on x (or vice versa) leads to a systematic error on the slope...



Negligible difference in most cases...

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Characteristics of regression y/x:

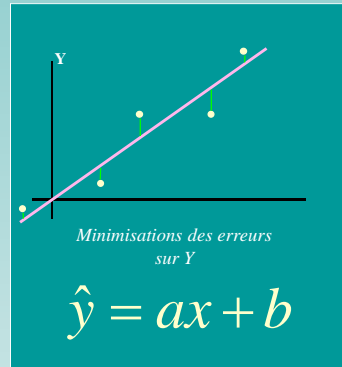
- Estimations of a and b:

$$a = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2} = \frac{\text{Cov}(x, y)}{\text{Var}(x)}$$

$$b = \bar{y} - a\bar{x}$$

Excel calculation using:

- Trend curve
- LINEST (French, droitereg)



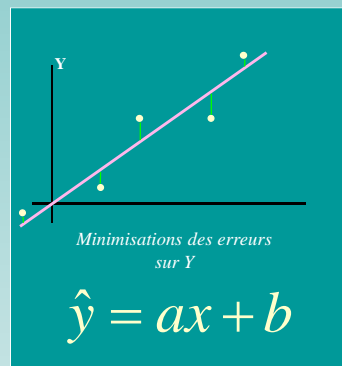
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Measurement-related error:

Error that we would have even if the model were perfect, because of the random error on x...

Standard deviation of residuals:

$$s_{y/x} = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n-2}} \quad (\text{function linest})$$



S.D. of the measurement error
= S.D. of prediction that we would have (same conditions) if the model was error-free!

But the model is never error-free!

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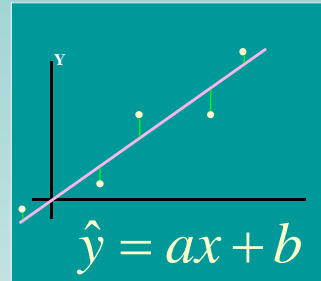
Modelisation error:

The model ($\hat{y} = ax + b$) can't be perfect since it is made from experiments...

- Estimation uncertainties of a and b:

Standard deviation of the slope a:
$$s_a = \frac{s_{y/x}}{\sqrt{\sum_i (x_i - \bar{x})^2}}$$

Standard deviation of the intercept b:
$$s_b = s_{y/x} \sqrt{\frac{\sum_i x_i^2}{n \sum_i (x_i - \bar{x})^2}}$$



Excel calculation using the function « linest » (french « droitereg »)

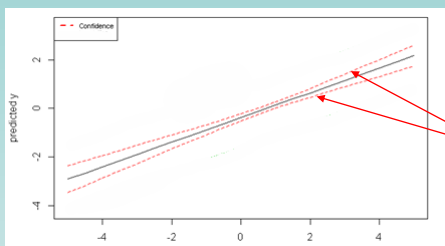
Final error = "Measurement-related error" + "Model error"

$$\text{Final uncert.} = \sqrt{(\text{Final error} = \text{"Meas.-related uncert."})^2 + (\text{Model error uncert.})^2}$$

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Uncertainty of prediction of a linear model

$$I(\text{pred})^2 = I(\text{meas})^2 + I(\text{modelisation})^2$$



$$I(\hat{Y}) = t \cdot s_{y/x} \sqrt{1 + \frac{1}{m} + \frac{(X - \bar{x})^2}{\sum (x_i - \bar{x})^2}}$$

↑ Meas. ↑ Model

- m = nb calibration samples
- x_i = calibration values, which mean is \bar{x}
- X = X Value of prediction sample
- $s_{y/x}$ = Standard deviation of residuals

- Depends (a little...) on X

- If « perfect » model (or m great), $I(\hat{Y}) = t \cdot s_{y/x}$

- Uncertainty increases if X goes away from \bar{x} (problem of extrapolation)

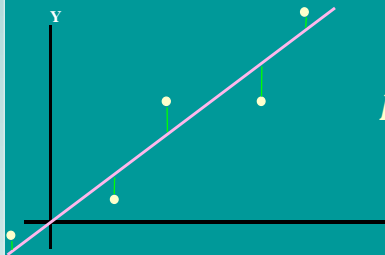
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TP6

Measuring the fit quality of a linear regression:

$$\text{Var}(Y) = \text{Var}(aX+b) + \text{Var}(\varepsilon)$$

Total information = modelised information + residual information



Coef. of determination:

$$R_d = \frac{\text{Var}(\text{modelised info})}{\text{Var}(\text{total info})}$$

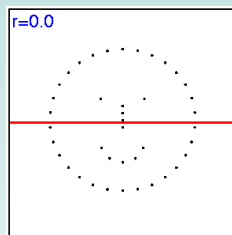
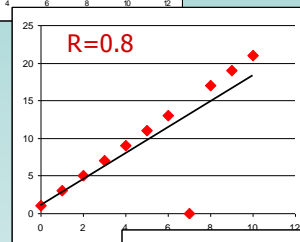
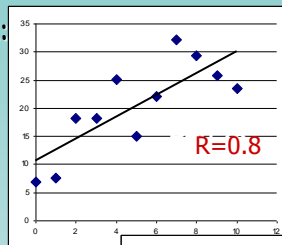
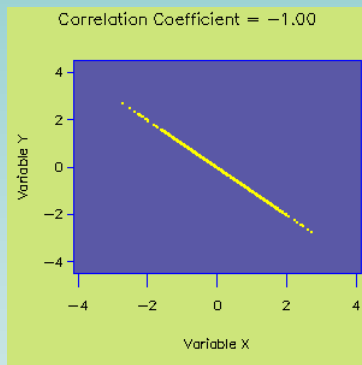
Correlation coef.

$$R_d = R_c^2$$

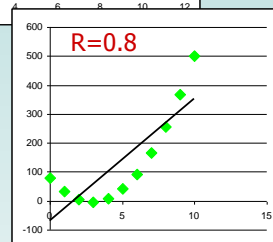
$$R_c = \frac{\text{Cov}(X, Y)}{\sigma(X)\sigma(Y)}$$

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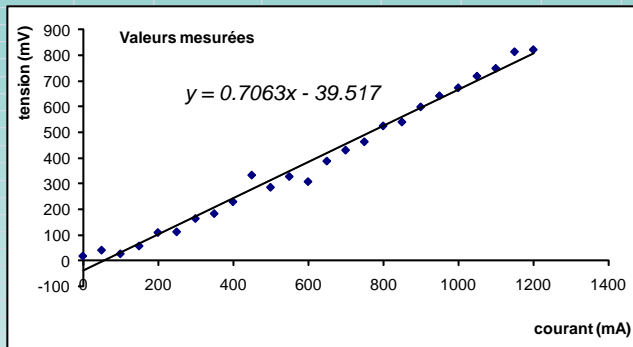
The correlation coef. Usage:



The correlation coefficient is only used to quantify the linear relationships between X and Y variables with random errors.



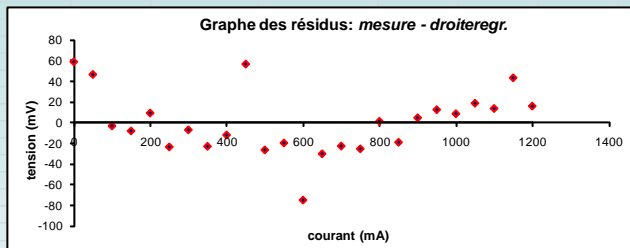
Linear regression: residuals analysis



Residuals = information not modelised, ideally random error

$$R_i = y_i - (a \cdot x_i + b)$$

Detection of outliers
To be removed after verification and with care...



Verification of linearity
Possibly to be corrected with non-linear regression

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Other behavioural modelling methods:

- Multivariates:
 - Linear multivariate
 - Multivariate regression, principal components analysis
 - Partial Least Squares (PLS)
 - Neural Network
- Non-linear monovariate
- Polynomial, power distribution, any function

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Linear multivariate regression, simplified approach:

- n Xvariables, p experiments (or samples)

Écriture matricielle pour les p expériences:

$$Y = A \cdot X + \varepsilon_y \quad \text{To be minimised}$$

$$\begin{cases} y_1 = a_1 x_{1,1} + \dots + a_n x_{n,1} + \varepsilon_1 \\ y_p = a_1 x_{1,p} + \dots + a_n x_{n,p} + \varepsilon_p \end{cases}$$

➤ $p < n$: no solution...

➤ $p = n$: maybe a solution:

$$A = Y \cdot X^{-1} \quad \text{Residual } \varepsilon_y \text{ nul...}$$

(Ex: 2 points to determine 1 straight line...)

➤ $p > n$: X not square...

But maybe even a least-squares solution!

$$A = Y \cdot X^T \cdot (X \cdot X^T)^{-1}$$

$X^T \cdot (X \cdot X^T)^{-1}$ is called « pseudo-inverse » of X

➔ •Excel « LINEST » function

Points developed at the end of TB...

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Non-linear regression (simplified...)

model $Y = F(X)$, F not linear

1: Linearization of the problem by variable change

Beer-Lambert: $I(\lambda) = I_0(\lambda) \exp(\beta(\lambda) \cdot C)$, non linéaire...

devient linéaire si on prend comme Xvariables les absorbances $A(\lambda) = -\log_{10}(I(\lambda)/I_0(\lambda))$

2: polynomial regression

"Any continuous function can be approximated using a polynomial"

Principle: add quadratic variables to obtain a linear combination, and apply linear methods

ex: $Y = f(x_1, x_2)$ not linear can be « approximated » by:

$$Y = a_{1,1}x_1 + a_{1,2}x_2 + a_{2,1}x_1^2 + a_{2,2}x_2^2 + b_{1,2}x_1x_2 \text{ etc...}$$

x_1, x_2, x_1^2, x_2^2 et x_1x_2 are linearly independant...

➔ Multilinear regression...

➔ Excel trend curve

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Biblio & links

Books:

"Statistics for analytical Chemistry" 3 rd ed. J.C. Miller and J.N. Miller John Wiley & Sons, 1998, la Bible...

"Multivariate Statistical Methods, A Primer" B.F.J. Monley, Chapman & Hall 1986.

"Modélisation et estimation des erreurs de mesure", M Neuilly, CETAMA, Lavoisier, Paris 1993.

Websites:

<http://physics.nist.gov/cuu/Uncertainty/index.html>: An excellent, simple and succinct site, but a reference on the calculation of uncertainties, this document was very much inspired by it. A more complete statistics course is available at : <http://www.itl.nist.gov/div898/handbook/>

<http://www.deltamu.fr/Publications>: Deltamu, SMEs in metrology offering many resources

<http://statpages.org/javasta2.html>: Collection of links and especially of Freewares on stats
<http://www.jybaudot.fr/General/indexstats.html>: Website of Jean-Yves Baudot with precise faith, popularizer and fun, a challenge in statistics!