



457.309 Hydraulics and Laboratory

.05.03 Uncertainty Analysis (3)



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(2019.03.12)



Today's objectives

- Final data handling and presentation without extra uncertainties.



Statistical rejection of “Bad” Data: *Chauvenet’s Criterion*

- Occasionally, when a sample of N measurements of a variable is obtained, there may be one or more that appear to differ markedly from the others.
- If some extraneous influence or mistake in experimental technique can be identified, these “bad data” or “wild points” can simply be discarded.
- More difficult is the common situation in which no explanation is readily available. In such situations, the experimenter may be tempted to discard the values on the basis that something must surely have gone wrong.
- However, this temptation must be resisted, since such data may be significant either in terms of the phenomena being studied or in detecting flaws in the experimental technique.

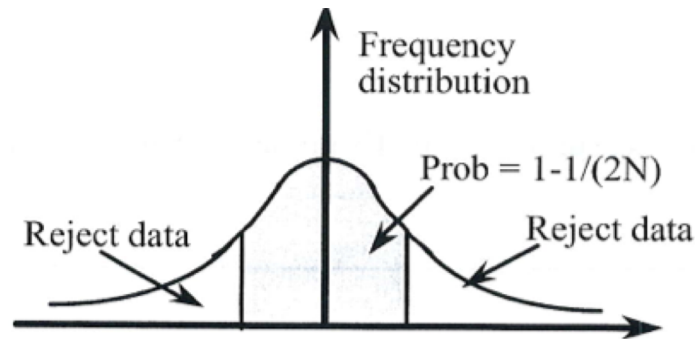


Statistical rejection of “Bad” Data: *Chauvenet’s Criterion*

- On the other hand, one does not want an erroneous value to bias the results. In this case, a *statistical* criterion must be used to identify points that can be considered for rejection. There is no other justifiable method to “throw away” data points.
- One method that has gained wide acceptance is *Chauvenet’s criterion*; this technique defines an acceptable scatter, in a statistical sense, around the mean value from a given sample of N measurements.
- The criterion states that all data points should be retained that fall within a band around the mean that corresponds to a probability of $1 - 1/(2N)$. In other words, data points can be considered for rejection only if the probability of obtaining their deviation from the mean is less than $1/(2N)$.



Statistical rejection of “Bad” Data: *Chauvenet’s Criterion*



- The probability $1-1/(2N)$ for retention of data distributed about the mean can be related to a maximum deviation from the mean, d_{max} , using the Gaussian probabilities.
- For the given probability, the nondimensional maximum deviation τ_{max} can be from the table where

$$\tau_{max} = \frac{\left| (X_i - \bar{X}) \right|_{max}}{S_X} = \frac{d_{max}}{S_X}$$

and S_X is the precision index of the sample.



Statistical rejection of “Bad” Data: *Chauvenet’s Criterion*

- Therefore, all measurements that deviate from the mean by more than $\tau_{max} S_X$ can be rejected. A new mean value and a new precision index can then be calculated from the remaining measurements.
- No further application of the criterion to the sample is allowed; **Chauvenet’s criterion may be applied only once to a given sample** of readings.

Chauvenet's Criterion for Rejecting a Reading	
Number of Readings (<i>N</i>)	Ratio of Maximum Acceptable Deviation to Precision Index (d_{max}/S_X)
3	1.38
4	1.54
5	1.65
6	1.73
7	1.80
8	1.87
9	1.91
10	1.96
15	2.13
20	2.24
25	2.33
50	2.57
100	2.81
300	3.14
500	3.29
1,000	3.48

Determine using
Gaussian probability



Example

Example. For the 10 temperature measurements in the first example, determine if any should be rejected by Chauvenet's criterion.

Solution) Inspecting the data from the first example, the fifth reading of $T=98.5^{\circ}\text{F}$ appears to deviate substantially from the others and is therefore a candidate for rejection. From the table above for $N=10$, the maximum dimensionless deviation is $d_{\max}/S_X=1.96$. Since $S_X \sim 0.49^{\circ}\text{F}$ in this case, $d_{\max} = 1.96S_X = (1.96)(0.49) = 0.96^{\circ}\text{F}$. The deviation for the fifth reading is 1.125°F so it can indeed be rejected, although no others can. Eliminating this point and recalculating the mean and precision index results in

$$\bar{X} = 97.25^{\circ}\text{F}$$

$$S_X = 0.31^{\circ}\text{F}$$

Comparing these values with those calculated in the first example, \bar{X} is decreased by only about 0.13% while S_X is decreased by over 37%.



Numerical Precision of Reported Results

- Except for a few constants such as π , all numerical values used in engineering computations are known to limited precision.
- Indeed, most engineering measurements are valid to 2, 3, or 4 digits at best, meaning that the digit that should appear in the third, fourth or fifth place, respectively, is somewhat unsure.
- If substantial information is available from which a good estimate of the uncertainty in a measurement can be obtained, for example from the detailed analysis described in preceding sections, then this uncertainty should be stated explicitly, together with the confidence level, if available.
- As an example of this approach, the drag coefficient in the previous example was found to be $C_D = 0.510 \pm 0.058$ at the 95% confidence level.



Numerical Precision of Reported Results

- Lacking such explicit detailed uncertainty specification, then the number of significant digit written from a numerical value implicitly specifies the uncertainty.
- For example, a length measurement stated as 10.2 m generally implies that the value is believed to be between 10.15 and 10.25 m. Therefore, the number of significant digits used in reporting numerical values should be limited to that which is truly reflective of the uncertainty in the value.
- The common practice of writing 10 significant digits for a value resulting from a series of calculations just because they appear on a calculator display is generally totally unfounded; the values in most engineering applications are not known with anywhere near this precision.



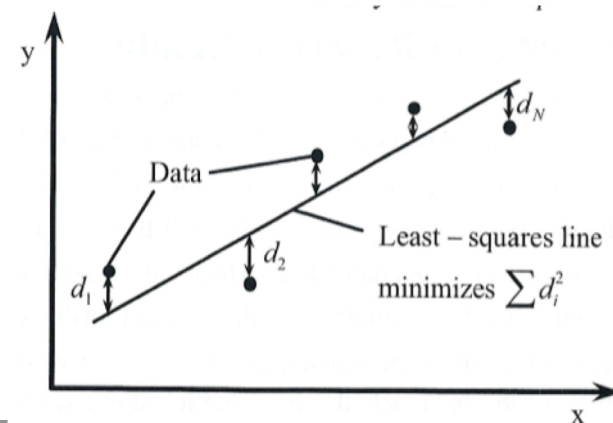
Numerical Precision of Reported Results

- Another rule-of-thumb to keep in mind is that *the number of significant digits used for the result of a calculation should not exceed the number of significant digits for the least precise quantity used in the calculation.*



Least Squares Curve Fitting

- Supposed that a set of data in two variables x and y has been obtained where x is the independent variable and y is the dependent variable.
- It is desired to obtain a simple analytical expression (or correlation equation) to represent these data. The question arises, “ what is the ‘best’ equation or ‘best’ curve through the data?” The criterion used most often to determine the “best fit” is the least-squared criterion.
- The least-squares method derives its name from the fact that the sum of the squares of the deviations between the data and the curve is minimized, as shown below.





Least Squares Curve Fitting

- In the following discussion it is assumed that the “true” relationship between x and y is linear, i.e. the best fit straight line through the data is sought. Although this is a common situation, the analysis below can also be extended easily to more complex curves.
- In addition, it is assumed that all of the uncertainty in the measurements is concentrated in the dependent variable y and that the uncertainties for all measured y values are equal.
- An equation of the form $y=ax+b$ is sought which minimized the sum of the squared deviations

$$S = \sum_{i=1}^N d_i^2 = \sum_{i=1}^N [y_i - (ax_i + b)]^2$$



Least Squares Curve Fitting

- In order to accomplish this, the partial derivatives are set to zero. This leads to

$$\frac{\partial S}{\partial a} = 0 \quad \Rightarrow \quad a \sum x_i^2 + b \sum x_i = \sum x_i y_i$$

$$\frac{\partial S}{\partial b} = 0 \quad \Rightarrow \quad a \sum x_i + bN = \sum y_i$$

- Solving for a and b simultaneously yields (all summations run from i =1 to N)

$$a = \frac{N \sum x_i y_i - (\sum x_i)(\sum y_i)}{N(\sum x_i^2) - (\sum x_i)^2} \quad \text{and} \quad b = \frac{(\sum x_i^2)(\sum y_i) - (\sum x_i)(\sum x_i y_i)}{N(\sum x_i^2) - (\sum x_i)^2}$$

- $y=ax^2+b$ can be treated in the same manner by regarding x^2 as the new variable. $\sin(x)$ or $\exp(x)$, etc. can be used similarly.