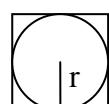


## Supplementary information

### Appendix A. Relation between uncertainty of sieve and mass

Considering a spherical particle of radius  $r$  which passes through the sieve square mesh of side  $l = 2r$  (case of circumference inscribed in a square).



Variations of volume are related to variation of radius as follows

$$dV = 4\pi r^2 dr \quad \text{a.1}$$

mass and volume are related through density ( $\rho$ )

$$m = \rho V \quad \text{a.2}$$

As a consequence variations of mass are related to variation of radius

$$dm = \rho dV \quad \text{a.3}$$

combining equations a.1 and a.3 we obtain

$$dm = \rho 4\pi r^2 dr. \quad \text{a.4}$$

Finally the uncertainty of the sieve can be expressed as:

$$u_{sieve} = \frac{dm}{m} = 3 \frac{dr}{r} \quad \text{a.5}$$

assuming a regular separations of the mesh equation a.5 is equivalent to

$$u_{sieve} = 3 \frac{dL}{L}$$

where  $L$  is the sieve length

## Appendix B. Calculation of the standard deviation for a function of $q$ variables

Let  $f(x_1, x_2, \dots, x_q)$  a function of  $q$  variables  $x_i$  each associated to an error given by the associated standard deviation

$\sigma_{x_i}$  of the corresponding measurement procedure. Where the standard definitions of  $\sigma_X$  is given by:

$$\sigma_X = \sqrt{\frac{1}{n-1} \sum_i^n [X_i - \bar{X}]^2} \quad b.1$$

where  $X_i$  and  $\bar{X}$  are the  $i$ -th determination and the mean value of the variable  $X$ ,  $n$  the number of the evaluation of the variable. Generally the analytical form of the function  $f$  is unknown and a practical approximation is to replace it with the truncated first-order expansion of the corresponding Taylor series since is assumed that the displacements of the  $x_i$  variables respect to their corresponding means values are small. Under these hypothesis the expression of  $f$  becomes:

$$f(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_q) \approx f(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_q) + \left. \frac{\partial f}{\partial \vec{x}_1} \right|_{\vec{x}_1} (\vec{x}_1 - \vec{x}_1) + \left. \frac{\partial f}{\partial \vec{x}_2} \right|_{\vec{x}_2} (\vec{x}_2 - \vec{x}_2) + \dots + \left. \frac{\partial f}{\partial \vec{x}_q} \right|_{\vec{x}_q} (\vec{x}_q - \vec{x}_q). \quad b.2$$

With these approximation we have that:

$$\overline{f(\vec{x}_{1_i}, \vec{x}_{2_i}, \dots, \vec{x}_{q_i})} = f(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_q) \text{ and } \sigma_f = \sqrt{\frac{1}{n-1} \sum_i^n [f(\vec{x}_{1_i}, \vec{x}_{2_i}, \dots, \vec{x}_{q_i}) - f(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_q)]^2}$$

and for sake of simplicity, using the variance ( $\sigma_f^2$ ) of  $f$ , we derive the relations between the standard deviation of  $f$  and those of the variables  $x_i$ .

$$\begin{aligned}
 \sigma_f^2 &= \frac{1}{n-1} \sum_i^n [f(x_{1_i}, x_{2_i}, \dots, x_{q_i}) - f(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_q)]^2 \\
 &= \frac{1}{n-1} \sum_i^n \left[ \left. \frac{\partial f}{\partial x_1} \right|_{x_1} (x_{1_i} - \bar{x}_1) + \left. \frac{\partial f}{\partial x_2} \right|_{x_2} (x_{2_i} - \bar{x}_2) + \dots + \left. \frac{\partial f}{\partial x_q} \right|_{x_q} (x_{q_i} - \bar{x}_q) \right]^2 \\
 &= \frac{1}{n-1} \left[ \left( \left. \frac{\partial f}{\partial x_1} \right|_{x_1} \right)^2 \sum_i^n (x_{1_i} - \bar{x}_1)^2 + \left( \left. \frac{\partial f}{\partial x_2} \right|_{x_2} \right)^2 \sum_i^n (x_{2_i} - \bar{x}_2)^2 + \dots + \left( \left. \frac{\partial f}{\partial x_q} \right|_{x_q} \right)^2 \sum_i^n (x_{q_i} - \bar{x}_q)^2 \right] + \\
 &\quad + \frac{2}{n-1} \left[ \left. \frac{\partial f}{\partial x_1} \right|_{x_1} \left. \frac{\partial f}{\partial x_2} \right|_{x_2} \sum_i^n (x_{1_i} - \bar{x}_1)(x_{2_i} - \bar{x}_2) + \dots + \sum_{r \neq s}^n \left. \frac{\partial f}{\partial x_r} \right|_{x_r} \left. \frac{\partial f}{\partial x_s} \right|_{x_s} (x_{r_i} - \bar{x}_r)(x_{s_i} - \bar{x}_s) + \dots \right. \\
 &\quad \left. + \sum_i^n \left. \frac{\partial f}{\partial x_{q-1}} \right|_{x_{q-1}} \left. \frac{\partial f}{\partial x_q} \right|_{x_q} (x_{(q-1)_i} - \bar{x}_{q-1})(x_{q_i} - \bar{x}_q) \right]
 \end{aligned}$$

where using the standard deviation definition (a.1) and those of the covariance between two variables X, Y:

$$\sigma_{X,Y} = \frac{1}{n-1} \sum_i^n [X_i - \bar{X}] \cdot [Y_i - \bar{Y}] \quad b.3$$

we obtain that:

$$\sigma_f^2 = \sum_k^q \left( \left. \frac{\partial f}{\partial x_k} \right|_{x_k} \right)^2 \sigma_{x_k}^2 + 2 \sum_{r,s}^{[q(q-1)/2]} \left. \frac{\partial f}{\partial x_r} \right|_{x_r} \left. \frac{\partial f}{\partial x_s} \right|_{x_s} \sigma_{x_r, x_s}. \quad b.4$$

Equation a.4 show the relations that we are looking for between the variance of the  $f$  values respect to those of the single variables  $x_i$ , and of the covariance from the couples  $(x_i, x_j)$ . If the errors associated to the two variables are randomly distributed and not correlated the covariance  $\sigma_{x_i, x_j}$  results to be equal to zero on the other hand if the two distributions

are strongly correlated we have that  $\sigma_{x_i, x_j} = \pm \sigma_{x_i} \sigma_{x_j}$  [1] and more generally holds that:

$$|\sigma_{x_i, x_j}| \leq \sigma_{x_i} \sigma_{x_j} \quad b.5$$

independently from the correlations and distributions of the  $x_i$  and  $x_j$  errors.

So we could have two possibly limit values of the  $f$  variance which easily follows from equation a.4:

$$\sigma_f = \sqrt{\sum_k^q \left( \frac{\partial f}{\partial x_k} \Big|_{x_k} \right)^2 \sigma_{x_k}^2} \quad \text{if the } x_k \text{ variables are uncorrelated}$$

$$\sigma_f = \sum_k^q \left| \frac{\partial f}{\partial x_k} \Big|_{x_k} \right| \sigma_{x_k} \quad \text{if the } x_k \text{ variables are strongly correlated}$$

Now we could consider as example the following case where the function  $f$  is defined as:

$$f(x, y) = \frac{x}{y}$$

and the  $x$  and  $y$  standard deviations are respectively:  $\sigma_x = \sqrt{\sigma_a^2 + \sigma_y^2}$  and  $\sigma_y$ . According to equation b.4 we have

that:

$$\sigma_f^2 = \left( \frac{1}{y} \right)^2 \sigma_x^2 + \left( -\frac{x}{y^2} \right)^2 \sigma_y^2 + 2 \left( \frac{1}{y} \right) \left( -\frac{x}{y^2} \right) \sigma_{x,y}$$

and using the inequality a.5 and dividing for  $f^2$  easily follows that:

$$\left( \frac{\sigma_f}{f} \right)^2 \leq \left( \frac{\sigma_x}{x} \right)^2 + \left( \frac{\sigma_y}{y} \right)^2 + 2 \left| \left( \frac{\sigma_x \sigma_y}{xy} \right) \right|$$

moreover if  $\sigma_a > \sigma_y$  and assuming the strong correlation we obtain:

$$\left( \frac{\sigma_f}{f} \right)^2 = \left( \frac{\sigma_a}{x} \right)^2 + \left( \frac{\sigma_y}{y} \right)^2 + 2 \left| \left( \frac{\sigma_a \sigma_y}{xy} \right) \right| \cong \left( \frac{\sigma_a}{x} \right)^2 + 2 \left| \left( \frac{\sigma_a \sigma_y}{xy} \right) \right|$$

see equation 8 of main text.

If  $\sigma_y$  it is negligible we have

$$\left( \frac{\sigma_f}{f} \right)^2 = \left( \frac{\sigma_a}{x} \right)^2$$

see equation 10 of main text