Quantification of uncertainty in zero-flow pressure approximation due to short-term wind fluctuations

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ABSTRACT

Uncertainties in airtightness measured using fan pressurization test should not be defined by the scattering of the points around the line defined using ordinary least square method anymore. Its definition requires first to know the uncertainties in pressure and airflow measurements. This works aims at quantifying one of the component of the envelope pressure uncertainty: the uncertainty in zero-flow pressure approximation due to short-term fluctuation of wind speed and direction. This is done by statistically analysing the approximation quality of 40 zero-flow pressure tests performed on 30 different units on eight different sites in Brussels. First, the analysis showed that this component of uncertainty could be slightly reduced by increasing the period of measurement used to compute zero-flow pressure approximation from 30 to 60 seconds. Second, it allowed to study the impact of multiple variables on the quality of the zero-flow pressure approximation. Third, it allowed to develop three different models to predict approximation quality as a function of different variables. This study suffers from some limitations due to the sample of units tested available. These limitations lead to important further work: the validation of the model on other samples of building tested and the adaptation of these models if needed. Further work should also focus on integrating these results on the uncertainty in envelope pressure measurements and the on uncertainty in airtightness estimation of the building.

KEYWORDS

Airtightness measurement; Uncertainties; Zero-flow pressure; Fan pressurization test.

1 INTRODUCTION

To be reliable, a measured quantity should always be given with its uncertainty. When performing a fan pressurization test, the uncertainty is often given as a function of the scattering of the data around the linear model obtained with an Ordinary Least Square (OLS) method. However, multiple authors showed that the uncertainties obtained with OLS method were not reliable in the case of airtightness measurements (Okuyama and Onishi 2012, Delmotte 2017, Prignon, Dawans et al. 2018). Uncertainty of regression parameters and airflow at a given pressure difference should be computed using other regression techniques as such as the Iterative Weighted Least Square (IWLS) or the Weighted Line of Organic Correlation (WLOC). In these cases, the uncertainty of regression parameters depends on the uncertainty of airflow and pressure measurements.

One of the main source of uncertainty is the fluctuation of reading in the pressure measurements due to variation in wind speed and direction (Sherman and Palmiter 1995). Unfortunately, the pressure difference due to climatic conditions (i.e., the zero-flow pressure) cannot be measured during a fan pressurization test. In the European ISO 9972:2015 standard (ISO-9972 2015) the pressure due to climatic conditions during the test is computed as the average of the zero-flow pressure measured before and after the measurement of airflow – pressure difference couples.

This approximation suffers from two uncertainties. The first is due to short-term fluctuations of wind speed and direction: the zero-flow pressure is considered constant while, in reality, it varies randomly during the test. The second is due to long-term fluctuations of wind speed and direction: the zero-flow pressure computed based on pre- and post-test measurements (i.e., the zero-flow pressure approximation) does not always fit with the average zero-flow pressure during this period.

In a previous work, we developed a method to quantify the uncertainties in zero-flow pressure due to short-term fluctuations of wind speed and direction. In the same work, we applied this method on a series of 30 tests performed on the same apartment. This research consists in applying the same method on 40 zero-flow pressure tests performed on 30 different units (i.e. apartment, school, single-family house, etc.) in eight different sites in Brussels. It aims at finding a mathematical relation between this component of uncertainty and multiple variables easily available during a fan pressurization test.

The methodology section of this paper has four subsections that describe the zero-flow pressure test, the sample of buildings tested, the seven variables studied and the statistical tools used for the analysis of the results. The result section presents them in two steps: a general visualization of all the results and a study of the impact of different variables on the mathematical relation. All the results are presented in terms of "approximation quality" which is an indicator of the variation of the zero-flow pressure measurements. The discussion section translates the "approximation quality" indicator into uncertainty value. The conclusion presents briefly the results obtained, the impact of these results in the field of airtightness uncertainties, the limitations of the study related to the methodology and the relevant further work in the field.

2 METHODOLOGY

2.1 The Zero-Flow Pressure Test

Delmotte used the zero-flow pressure test for the first time in 2017 (Delmotte 2017). This test consists in measuring the zero-flow pressure every second during three different periods: two approximation periods and one fictitious period (Figure 1). The two approximation periods correspond to the zero-flow pressure measurements used to compute the zero-flow pressure approximation in a traditional fan pressurization test. In his work, Delmotte considered periods of 30 seconds while in this work two periods of 120 seconds are considered. This is because this paper focuses also on how approximation periods affects the uncertainty. The fictitious period corresponds to the time a fan pressurization test would take in practice. In this research, a fictitious period of 600 seconds is considered, as such as in the work of Delmotte.

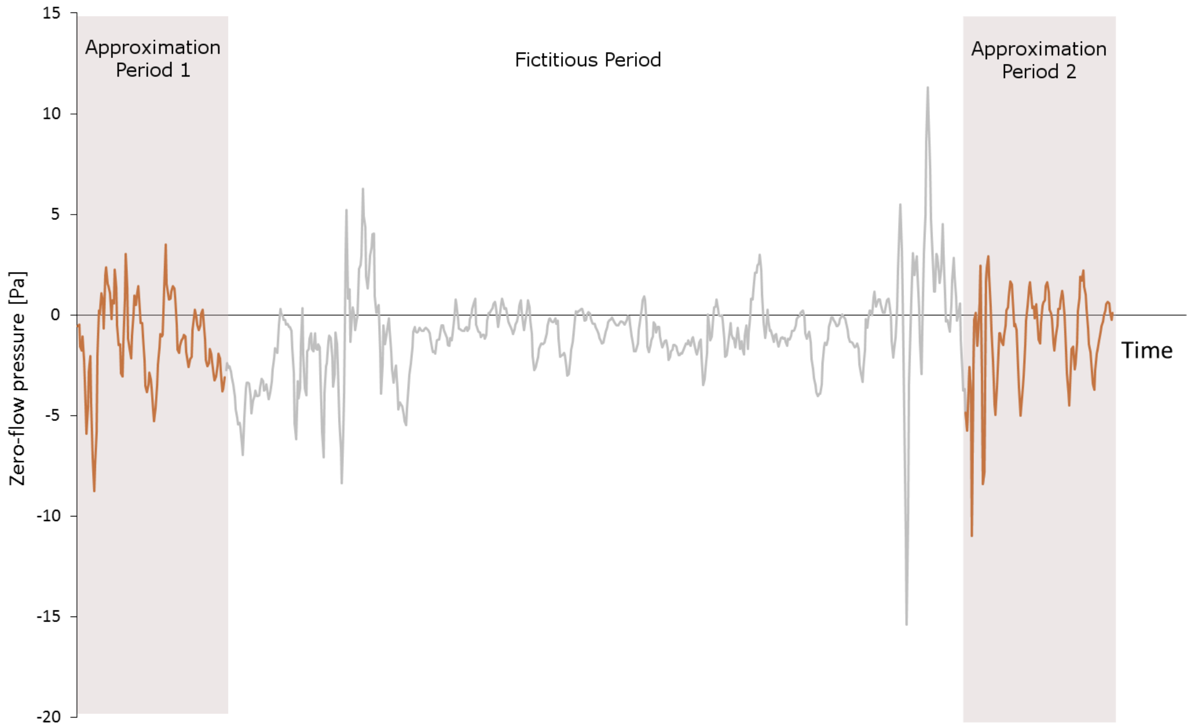


Figure 1 – illustration of the three successive periods of a zero-flow pressure test

The zero-flow pressure approximation is then computed based on measurements made during the approximation periods. This research deals only with the constant approximation method (i.e., the average of zero-flow pressure measurements made during both approximation periods). This is the method imposed by the ISO 9972:2015 standard.

Then, the zero-flow pressure approximation is compared to the zero-flow pressure measured every second during the fictitious period. The "approximation quality" (ε) is the average of the difference between approximated and measured zero-flow pressure (Equation 1).

$$\varepsilon = \frac{\sum_{i=1}^{600} |\Delta p_{0,i} - \Delta\widetilde{p_0}|}{600} \tag{1}$$

Where $\Delta p_{0,i}$ is the zero-flow pressure measured every second (i) during the fictitious period and $\Delta\widetilde{p_0}$ is the zero-flow pressure approximation based on measurements made during approximation periods.

2.2 Description of Buildings Tested

The four pie charts in Figure 2 represent the repartition of four different variables among the 40 units tested: the type of unit measured, the storey where the measurement was taken, the volume of the unit and the type of construction.

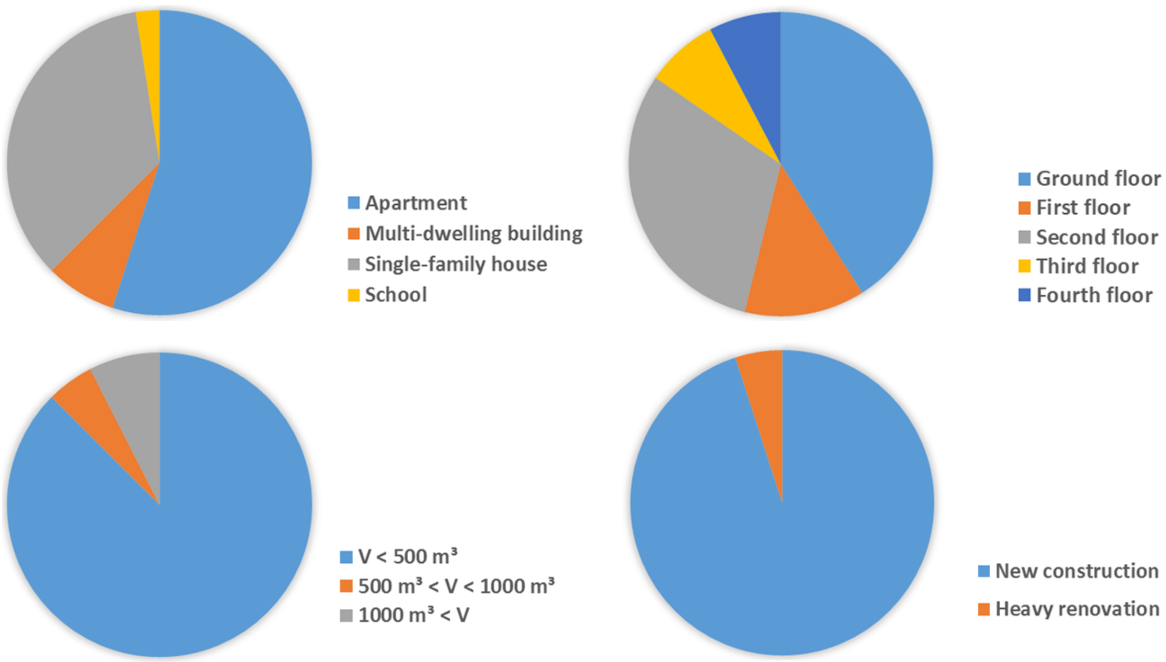


Figure 2 – repartition of the sample of units tested regarding four variables: type of units, storey of the measurement, volume of the unit and type of construction

It is important to point out that, in the sample of units available for the tests there are only one non-residential unit (school). In addition, almost all tests (38) were performed on new constructions and only five units have a volume higher than 500 m³. These limitations related to the sample are tackled in the conclusion of this work.

2.3 Variables analysed

The impact of 7 different variables was studied: the value of the zero-flow pressure approximation ($\Delta P_{0,a}$ in Pa), the difference between zero-flow pressure measured during first and second approximation periods (Δ in Pa), the standard deviation of the measurements used to compute zero-flow pressure approximation (σ in Pa), the wind speed obtained from the closest weather station available (w in km/h), the volume of the unit (V in m³), the storey where the measurement is taken (s in storey) and the temperature difference between inside and outside during the test (ΔT in °C). These seven variables were selected because they are easy to obtain in practice except for the wind speed that can be sometimes difficult to get. All these variables were tested for four different durations of approximation periods: 30 seconds, 60 seconds, 90 seconds and 120 seconds.

The wind speed is the only variable that was not directly available on site during the test. However, it was still considered in the variables because of its well-known impact on the pressure measurement uncertainty (Sherman and Palmiter 1995, Carrié and Leprince 2016). The distance between the closest weather station and the site varied between 300 and 1500 meter, and the data given is the average of one hour of wind speed measurement. In addition, the weather stations are often placed on the roof of a building and therefor it does not take into account the surroundings of the tested unit. However, this study is not interested in the physical impact of wind speed and wind pressure on the uncertainties but in a quantification of uncertainties based on data available during a fan pressurization test. These kind of simple climatic data are often easily available for free.

2.4 Statistical analysis

The statistical analysis aims at finding which variables have a significant impact on the approximation quality (ε – Equation 1) and at deducing a relation between the approximation quality and these variables.

In the previous section, seven variables are described while there should be eight. Indeed, the duration period is considered differently than other variables. This is because of the dependency implied by the experimental design. For each test, the four duration periods are computed using the same set of data. Therefore, the impact of duration period cannot be deduced the same way than other variables. When data are nested (i.e., the duration of approximation periods are nested within the different tests), Multi-Level Modelling (MLM) should be used (Rasbash, Steele et al. 2015) instead of classic statistical tools.

The use of MLM in zero-flow pressure tests was deeply investigated in our previous work. However, in this work the objective of MLM is to investigate if different models should be used for different approximation methods. It can be answered simply by assessing the need for MLM when considering only two levels: the duration period nested within the test ID.

MLM is needed when there is large intraclass correlation (ICC) (> 0.45) (Julian 2001) and when the design effect is higher than 2 (Muthén and Satorra 1995). ICC can be defined as the proportion of approximation quality variation that occurs across tests or as the expected correlation between the approximation qualities of the four duration of a same test (Peugh 2010). It is computed using Equation 2. τ_{00} is the variation of approximation quality between tests and σ^2 is the average of the approximation quality variation of different periods within each test. The design effect quantifies how the dependence of data affects the estimate of standard error. In other terms, it provides the multiplier to be applied to the standard error to take account for the nested structure of the data. It is computed using Equation 3with n_c the number of different periods measured by test (Hayes 2006, Peugh 2010).

$$ICC = \tau_{00}/(\tau_{00} + \sigma^2) \tag{2}$$

$$Design\ Effect = 1 + (n_c - 1) * ICC \tag{3}$$

In this study, τ_{00} is 0.79, σ^2 is 0.07 and n_c is 4. Therefore, ICC is 0.92 and Design effect is 3.76 and MLM is needed. This means that classic statistical tools cannot be used to study the impact of approximation period duration on the approximation quality because of the nested structure of data. Therefore, in this paper, the seven other variables are computed separately for the four different durations.

In such case, the seven other variables are not nested in a hierarchical structure anymore. Therefore, the statistical analysis can be made with classical statistical tool as such as multiple regression. It aims simply at finding the linear combination of predictors (i.e., the seven selected variables) that fits as much as possible the predictor (i.e., the approximation quality) (Field, Miles et al. 2012). A multiple regression provides the coefficients for each predictor in the linear model, but it also provides information on the statistical significance of these predictors (p-values) and the quality of the fitting of the model (multiple R^2). Multiple R^2 can be interpreted as such as the R^2 in a simple regression: it is the amount of variance in the outcome (i.e., the approximation quality) explained by the model (Field, Miles et al. 2012).

Four different multiple regressions were performed: one with all the variables, one with variables having a significant impact including wind speed, one with variables having a significant impact without wind speed and one with the standard deviation only. These four regressions were performed for the four different durations of the approximation periods.

3 RESULTS

3.1 General Results

Figure 3 shows the bar graph of the approximation quality of the 40 tests for the four different duration of approximation periods. The period of 30 seconds is slightly worse than other periods, but all results remain in the same order of magnitude.

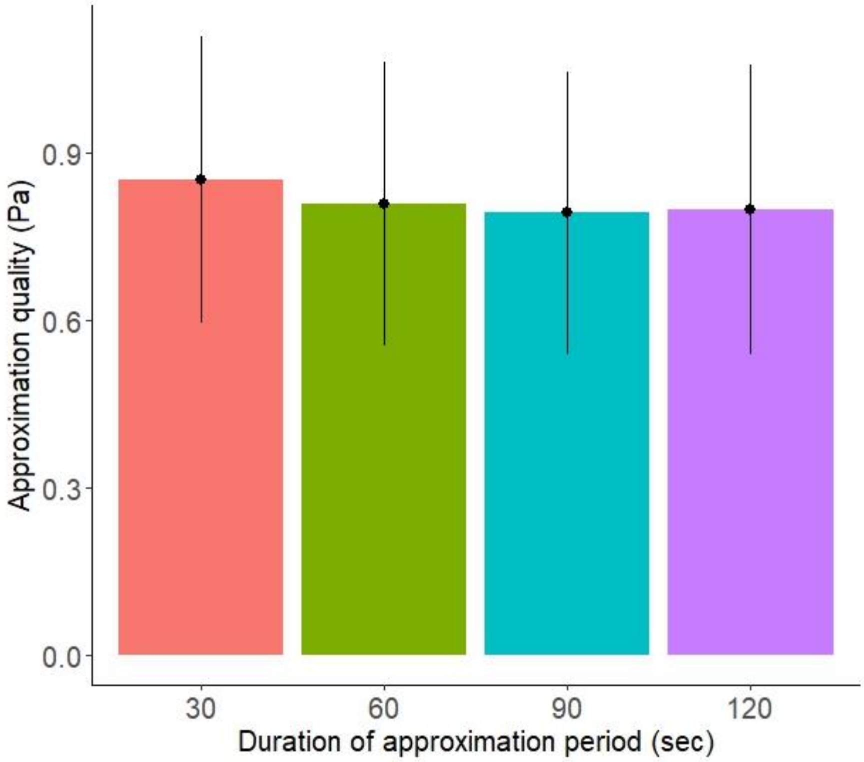


Figure 3 – bar graph of the 40 approximation qualities computed for the four different approximation periods

Table 1 presents the difference of mean of approximation quality for the four duration and the statistical significance of this difference, using pairwise wilcoxon rank-sum test with Bonferroni correction. The comparison is made using Wilcoxon rank-sum test because data follow a distribution significantly different from normal (Shapiro-Wilk $= 0.82, p < 0.001$). In addition, since multiple comparisons were performed on the same data, Bonferroni corrections are applied to counterbalance the increase in familywise error rate. The familywise error is the increasing probability of making a Type I error (i.e. the probability of falsely rejecting the null hypothesis), and is calculated as $1 - 0.95^n$ with n being the number of comparisons performed (Field, Miles et al. 2012). The probability of making a Type I error is 26%. The Bonferroni correction ensures that the cumulative Type I error rate is kept below 0.05 and is computed as α/k where k is the number of comparison.

Table 1 - results of the comparison using pairwise Wilcoxon rank-sum test with Bonferroni correction. Results are highly significant (***), significant (**), slightly significant (*) or non-significant (N.S.)

vs	30	60	90
60	0.04 *		
90	0.06 **	0.02 N.S.	
120	0.05 *	0.01 N.S.	-0.01 N.S.

Results show that only the comparisons including 30 second periods are statistically significant (30vs90) or slightly significant (30vs60 and 30vs120). Other comparisons are statistically non-significant.

3.2 Multiple Regression

This section presents and analyses the results of the four multiple regressions performed for each of the four durations. Table 2, Table 3 and Table 4 provide the coefficients and the statistical significances of each variable and the multiple R^2 for each regression.

The first multiple regression (Table 2) shows that two variables have no significant impact on the approximation quality: the difference of approximation in the first and in the second duration period (Δ) and the temperature difference between inside and outside the unit during the test (ΔT). Variables having the most significant impact are the standard deviation of the measurements (σ) and the wind speed (w). The statistical significance of some variables ($\Delta P_{0,a}$, w, V and s) depends on the duration of the approximation periods. Good fitting is obtained (multiple R^2 between 0.75 and 0.79) when considering all the variables.

Table 2 - results of the multiple regression applied on all variables (7) for the four durations.

Variables	Period 30		Period 60		Period 90		Period 120	
Intercept	-1.2 e-00	**	-1.3 e-00	**	-1.2 e-00	**	-1.4 e-00	**
$\Delta P_{0,a}$	2.9 e-01	**	1.3 e-01	N.S.	1.2 e-01	N.S.	1.0 e-01	N.S.
Δ	-3.1 e-01	N.S.	-3.1 e-01	N.S.	-3.0 e-01	N.S.	-3.1 e-01	N.S.
σ	1.1 e-00	***	9.5 e-01	***	9.6 e-01	***	8.8 e-01	***
w	7.4 e-02	***	7.3 e-02	**	6.0 e-02	**	6.9 e-02	**
V	1.3 e-04	**	1.4 e-04	**	1.2 e-04	*	1.3 e-04	*
s	8.6 e-02	N.S.	1.0 e-01	N.S.	1.0 e-01	*	1.3 e-01	*
ΔT	8.9 e-04	N.S.	-3.7 e-03	N.S.	-2.0 e-03	N.S.	5.9 e-03	N.S.
Multiple R^2	0.77		0.79		0.76		0.75	

$p < 0.001$ (***) is highly significant, $p < 0.01$ (**) is significant, $p < 0.05$ (*) is slightly significant and $p > 0.05$ (N.S.) is not significant.

Conclusions on the statistical significance of the volume and the storey should be drawn carefully. Regarding the storey (s), it is important to keep in mind that the zero-flow pressure was measured higher than the fourth floor only once. Similar study performed on high-rise buildings would probably give different results since the wind speed has a different magnitude and the surroundings affect differently the wind pressure on the building. In addition, in high-rise buildings stack effect has a huge impact on the zero-flow pressure. Regarding the volume (V), only five units have a volume higher than 500 m³. Similar study performed on high-volume units could lead to different conclusions.

The second multiple regression (Table 3) confirms the first one: good fitting is obtained when removing the two non-significant variables (multiple R^2 between 0.73 and 0.74). The most significant variables are still the standard deviation of the measurement and the wind speed. The coefficients can be used to define a mathematical relation between the approximation quality and these five variables. Equation 4 gives this relation in the case of 30-second approximation periods.

$$\varepsilon = -1.2 + 0.30 * \Delta P_{0,a} + 0.85 * \sigma + 0.07 * w + 1.3\, e^{-4} * V + 0.12 * s \qquad (4)$$

Table 3 - results of the multiple regression applied on main variables, including wind speed (5) for the four durations.

Variables	Period 30		Period 60		Period 90		Period 120	
Intercept	-1.2 e-00	**	-1.3 e-00	**	-1.2 e-01	**	-1.4 e-00	***
$\Delta P_{0,a}$	3.0 e-01	**	1.3 e-01	N.S.	1.3 e-01	N.S.	1.2 e-01	N.S.
σ	8.5 e-01	***	7.8 e-01	***	8.1 e-01	***	7.7 e-01	***
w	7.4 e-02	***	6.9 e-02	**	6.2 e-02	**	7.3 e-02	***
V	1.3 e-04	**	1.4 e-04	**	1.2 e-04	*	1.2 e-04	*
s	1.2 e-01	*	1.2 e-01	*	1.3 e-01	*	1.5 e-01	**
Multiple R^2	0.74		0.73		0.74		0.73	

p < 0.001 (***) is highly significant, p < 0.01 (**) is significant, p < 0.05 (*) is slightly significant and p > 0.05 (N.S.) is not significant.

In the third multiple regression, the wind is removed from the variables since it is the only variable which is not directly available during a fan pressurization test. The impact of the standard deviation is found highly significant, but other terms are almost all found not significant. The value of the zero-flow pressure approximation is found slightly significant in the case of 30-second approximation periods only. The third multiple regression shows a larger decrease of the multiple R^2 (between 0.62 and 0.64) than the second one. However, the fitting is still good and the relation between approximation quality and multiple variables could be used even without considering wind speed. Similarly, to the second multiple regression, the third allows the deduction of a mathematical relation (Equation 5 – 30 second periods).

$$\varepsilon = 0.04 + 0.27 * \Delta P_{0,a} + 1.1 * \sigma + 8.6\, e^{-5} * V + 0.04 * s \qquad (5)$$

Table 4 - results of the multiple regression applied on main variables, without wind speed (4) for the four durations.

Variables	Period 30		Period 60		Period 90		Period 120	
Intercept	3.8 e-02	N.S.	-8.5 e-02	N.S.	-1.7 e-02	N.S.	-1.8 e-01	N.S.
$\Delta P_{0,a}$	2.7 e-01	*	9.9 e-02	N.S.	9.9 e-02	N.S.	9.2 e-02	N.S.
σ	1.1 e-00	***	9.9 e-01	***	1.0 e-00	***	9.7 e-01	***
V	8.6 e-05	N.S.	1.0 e-04	N.S.	7.8 e-05	N.S.	6.9 e-05	N.S.
s	4.3 e-02	N.S	5.3 e-02	N.S.	7.0 e-02	N.S.	7.7 e-02	N.S.
Multiple R^2	0.64		0.63		0.66		0.62	

p < 0.001 (***) is highly significant, p < 0.01 (**) is significant, p < 0.05 (*) is slightly significant and p > 0.05 (N.S.) is not significant

The last multiple regression shows that a simple linear model including only the standard deviation of the measurements as a predictor provides still good fitting (multiple R^2 between 0.55 and 0.61). The mathematical relation is highly simplified (Equation 6).

$$\varepsilon = 0.11 + 0.98 * \sigma \qquad (6)$$

Table 5 - results of the multiple regression applied on standard of the measurement only for the four durations.

Variables	Period 30		Period 60		Period 90		Period 120	
Intercept	1.1 e-01	N.S.	5.4 e-02	N.S.	-3.1 e-02	N.S.	-3.3 e-02	N.S.
σ	9.8 e-01	***	9.5 e-01	***	9.6 e-01	***	9.3 e-01	***
Multiple R^2	0.55		0.57		0.61		0.57	

p < 0.001 (***) is highly significant, p < 0.01 (**) is significant, p < 0.05 (*) is slightly significant and p > 0.05 (N.S.) is not significant

Although multiple R^2 has a clear meaning (i.e., the amount of variance explained by the model), it can be sometimes difficult to visualize what it means practically. Figure 4 shows the predicted approximation quality vs. the real approximation quality for the three cases when considering approximation periods of 30 seconds. The predicted values are obtained when applying Equation 4, Equation 5 and Equation 6, while the real values are the data used to develop the models. The difference in multiple R^2 values is probably due to the tests with high value of approximation quality. Indeed, the three points with high measured approximation quality are better predict with the first model (Equation 4) than with the second (Equation 5) and the third (Equation 6) model.

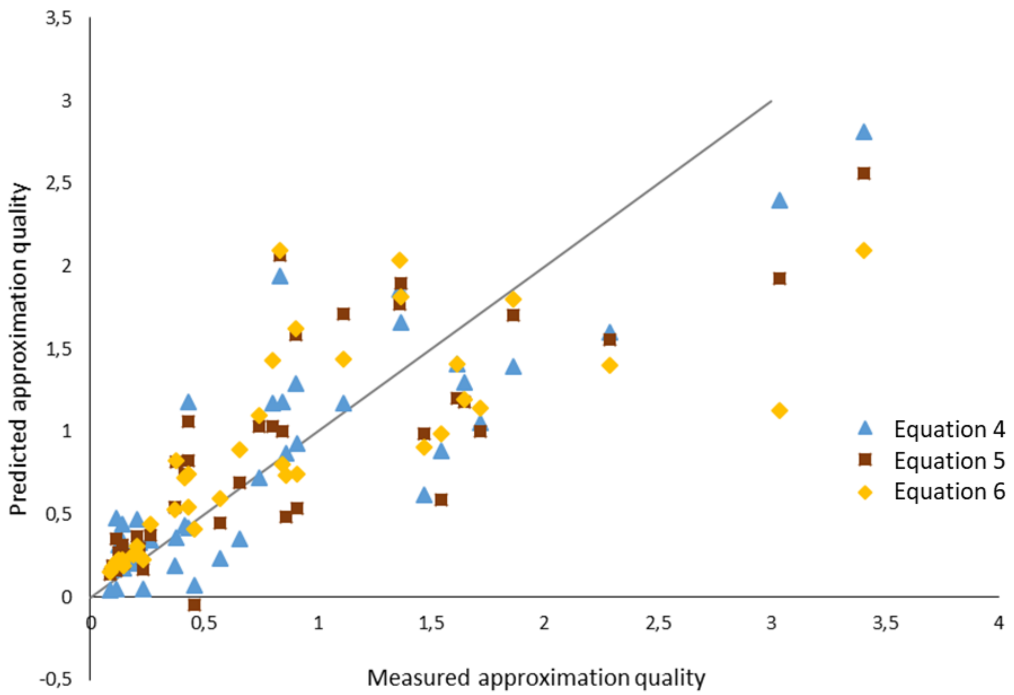


Figure 4 - representation of the predicted vs. measured approximation quality for the three models

4 DISCUSSION

Until here, this paper focuses on the approximation quality ε. But in practice, we are interested in uncertainty related to wind fluctuations.

In previous section, results are presented in terms of approximation quality. However, to be useful in practice, results should be presented in terms of uncertainty. This section discusses the steps and hypotheses to translate the results from approximation quality to uncertainty. On the one hand, it was shown in a previous work that the zero-flow pressure measured during the fictitious period follows a normal distribution. Therefore, it can be assumed that the uncertainty is the standard deviation of the zero-flow pressure measurements during the fictitious period $\sigma(\Delta P_0)$ (JCGM 2008).

On the other hand, ε is the average of the difference between approximated and real zero-flow pressure. Therefore, it is reasonable to assume assumed that $\Delta P_0 - \varepsilon/2$ and $\Delta P_0 + \varepsilon/2$ are the lower and the upper limit of the interval containing 50% of the zero-flow pressure measured during the fictitious period of the zero-flow pressure test.

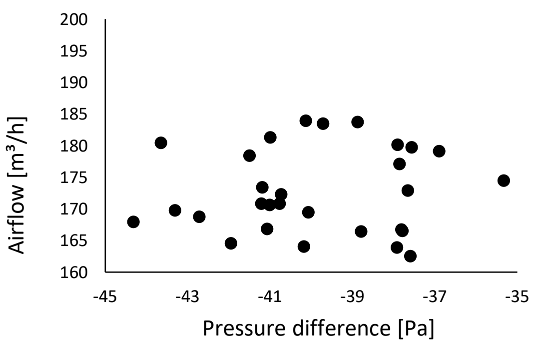
Since the Z scores of the normal distribution are respectively 0.675 and -0675 when considering 75% and 25% of the results, Equation 7 and Equation 8 can be used to link approximation quality and standard deviation.

$$0.675 = \frac{(\Delta P_{0,a}+\varepsilon/2)-\Delta P_0}{\sigma(\Delta P_0)} \qquad (7) \qquad\qquad -0.675 = \frac{(\Delta P_{0,a}-\varepsilon/2)-\Delta P_0}{\sigma(\Delta P_0)} \qquad (8)$$

It can be assumed that the zero-flow pressure approximation ($\Delta P_{0,a}$) equals the average of the zero-flow pressure measurements made during the fictitious period (ΔP_0). The assumption is made because this work computes the uncertainties due to short-term fluctuations of wind only. In practice there is also an uncertainty related to long-term wind fluctuations and both uncertainties should be propagated to derived the uncertainty in pressure measurements due to wind. However, with this assumption, it is possible to express the uncertainty in zero-flow pressure approximation due to short-term fluctuations of wind as a function of the approximation quality only (Equation 9).

$$u(\Delta P_{0,a}) = \sigma(\Delta P_0) = \varepsilon/1.35 \qquad (9)$$

In practice, each pressure difference – airflow couple is the average of multiple measurements. This reduces the impact of the uncertainty due to wind fluctuations. When data are uncorrelated, the uncertainty of an average is simply the uncertainty of one measurement divided by the number of measurements used for the average. However, it was already discussed by author previously (Delmotte 2013) and it does not seem a reliable assumption. Figure 5 shows the pressure difference – airflow couples measured during a pressurization measurement on the left and these couples if data were uncorrelated on the right.



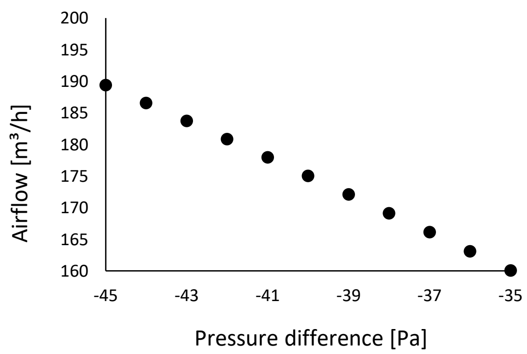


Figure 5 – airflow - pressure difference couples measured during a pressure measurement on the left and equivalent couples if data were uncorrelated

In addition, when performing a test, the operator often tries to take a measurement when wind fluctuations are low. It reduces the impact of wind fluctuations and decreases this component of the uncertainty. Therefore, one has to be careful when considering uncertainties related to short-term fluctuations of wind in practice: Equation 9 provides an upper limit of this uncertainty.

5 CONCLUSION

In this work, 40 zero-flow pressure tests were performed on different units. They were analysed with multi-level modelling and multiple regression. These statistical tools allow in a first step to study the impact of multiple variables on the quality of the zero-flow pressure approximation.

In a second step, they allow developing three different models to predict approximation quality as a function of different variables. Lastly, the discussion explains how to translate from “approximation quality” indicator to uncertainty.

This work is a step in the quantification of uncertainties in pressure measurements. Since this component was not considered before, it increases the computed pressure uncertainty and makes it non-negligible anymore. Therefore, ordinary least square regression method should not be used anymore. This results strengthens the trends among authors to suggest the use of alternative regression methods.

This research is limited by the set of data. As explained in the methodology section, the dataset contains only two renovations, five units with volume higher than 500 m³, one non-residential building and one building with more than four stories. In addition, the dataset was entirely used to create the model and none of them was used to validate the model. Therefore, further work should focus on the validation of the models suggested and, if needed, on their adaptation for high-volume and high-rise units.

Furthermore, this work focuses on one component of the uncertainty in fan pressurization testing. This uncertainty should be combined with other components in order to obtain the total uncertainty in pressure measurements. This is an important work because different sources of uncertainties could be correlated and the calculation of their propagation could require some investigation (JCGM 2008). An example of possible correlation is the uncertainties related to short-term fluctuations of wind and the uncertainties related to the long-term fluctuations of wind.

6 ACKNOWLEDGEMENTS

Authors want to thank the company *Jacques Delens* for its mobilization in this work and the availability of their construction sites. This work is part of the “AirPath50” project funded by INNOVIRIS.

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