Proposal for improving the linear regression method and uncertainty calculation in building airtightness tests

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ABSTRACT

Improving the energy efficiency of buildings and the quality of indoor air requires accurate assessments of airtightness. The conventional regression method, Ordinary Least Squares (OLS) regression—as shown in ISO 9972—encounters challenges in the occurrence of fluctuating wind conditions, affecting the reliability of air permeability measurements. This study explores the potential of alternative regression techniques, specifically Weighted Least Squares (WLS) and Weighted Line of Organic Correlation (WLOC), to enhance the precision and reliability of building airtightness tests across varied environmental settings. Through the analysis of a comprehensive dataset derived from over 6,000 on-site blower door tests conducted on a multitude of house configurations, this research assesses the relative accuracy of these methods. Additionally, it introduces a new approach to global uncertainty calculation for the WLOC method.

Findings indicate that while all methods exhibit similar in predicting the airflow at 50 Pa, WLS and WLOC_2 reduce prediction error by up to 6 percentage points at 4 Pa under wind speeds exceeding 4 m/s compared to other methods. At 50 Pa, the OLS 95% confidence interval covers the reference airtightness value for only 25% of the data, compared to WLOC_2 with 42% and WLS with 91%. At 4 Pa, while OLS interval covers only 21% of measurements, WLS overestimates uncertainty with 100% coverage, and WLOC_2 achieves 82% coverage. These results support incorporating weighted regression methods in airtightness testing standards.

KEYWORDS

Airtightness test, regression method, ISO 9972, WLOC

1 INTRODUCTION

ISO 9972 (*ISO 9972:2015*, 2015) employs a regression analysis to interpret measured pressure and airflow data, Recommending the Ordinary Least Squares (OLS) regression to the logarithms of the measured values in its Annex C . However, recent studies (Delmotte, 2017; Delmotte & Laverge, 2011; M. Sherman & Palmiter, 1995; Walker et al., 1998) have highlighted OLS's limitation in accurately representing pressure/flow data at data extremes (Prignon et al., 2020) or extrapolating to low pressures, leading to significant biases and large uncertainties at higher windspeeds (Kölsch & Walker, 2020, 2022). This is critical because envelope pressures associated with natural infiltration in buildings are often at low pressures below 5 Pa (Etheridge, 2015; M. H. Sherman & Chan, 2006), which is essential in energy performance codes in places like France (AFNOR, 2016; Moujalled & Mélois, 2023) and California (California Energy Commission, 2022). Moreover, OLS fails to propagate the uncertainty of pressure measurements accurately (Prignon et al., 2020).

The objectives of this paper are:

1. Propose a simple uncertainty calculation to be included in the weighting scheme for the WLOC method.
2. Conduct a comprehensive comparison of uncertainty calculations for regression methods as proposed in two existing standards (OLS_1 and WLS) and in line with the

"Guide to the expression of uncertainty in measurements" (GUM) (Joint & Committee for Guides in Metrology, 2008) for the OLS and WLOC regression methods.
3. Utilize an extensive dataset of over 6,000 blower door tests to assess each method's ability to accurately predict airflow values and estimate 95% confidence intervals.

2 METHOD

2.1 Description and limitations of existing alternatives for linear regression

The OLS regression method in Annex C of ISO 9972 minimizes the sum of squared residuals, which are the vertical distances between the measured values and the regression line. For this regression procedure, the pressure difference is defined as the independent variable and the air flow as the dependent variable assuming negligible error in pressure difference. However, fluctuations of wind speed and direction affect building pressure difference, causing higher relative uncertainty at lower pressures. Smaller measurement points, logarithmized before calculating the least squares fit, influence results more significantly.

To mitigate this effect, the German National Annex to ISO 9972 (*DIN EN ISO 9972:2018-12*, 2018) and the Canadian CAN/CGSB-149.10 standard (*CAN/CGSB-149.10-2019*, 2019) proposed the Weighted Least Square (WLS) regression, which weights pressure measurement data by the square of the volume flow, limiting the impact of measurements at lower pressures.

Okuyama et al. (Okuyama & Onishi, 2012) worked on an Iterative Weighted Least Squares (IWLS) approach, while Delmotte proposed the Weighted Line of Organic Correlation (WLOC) (Delmotte, 2017), which minimizes the sum of products of the weighted horizontal and vertical differences between the measured values and the predicted line, considering both pressure and airflow uncertainties are non-negligible and unequal in reality. In addition, WLOC includes a ponderation of each point according to their uncertainty: giving less weight to points with higher uncertainty.
WLOC would provide more reliable measurements at low pressure differences and better uncertainty estimation, which was supported by Prignon et al. (Prignon et al., 2018, 2020) and Kim et al. (Kim et al., 2022) in small-scale studies conducted in Belgium and Korea. However, these studies were limited by their dataset size.

2.2 New WLOC method

A new "WLOC_2" method introduced in this study calculates the uncertainties of pressure difference $u(\Delta p_i)$ and airflow $u(q_{\mathrm{env},i})$ using data available during a "normal ISO 9972" test without additional measurement requirement.
To account for pressure fluctuations during the test, we included the standard deviation of the measurement as the first term of Eq. (1). The second term incorporated the measurement device uncertainty specified by ISO 9972. The third term addresses the impact of pressure variation along the building façade, which we assume to be in the order of magnitude of the zero-flow pressure difference measured before and after the test.
Thus, the uncertainty of the pressure difference $u(\Delta p_i)$ is expressed as:

$$u(\Delta p_i) = \sqrt{\sigma^2(\Delta p_{\mathrm{m},i}) + u^2(\Delta p_{\mathrm{m},i}) + \left(\frac{\Delta p_{0,1} + \Delta p_{0,2}}{2}\right)^2} \qquad (1)$$

where $\sigma(\Delta p_{\mathrm{m},i})$ represents the standard deviation of the pressure measurement at each station. In this context, "station" means the series of measuring points at one pressure difference target. The maximum permissible measurement error (MPME) for the pressure measurement device is specified as 0.5 Pa with a resolution of 0.25 Pa.
The WLOC_2 uncertainties of airflow $u(q_{\mathrm{env},i})$ for pressurization (p) and depressurization (d) are defined as:

$$u(q_{\mathrm{env,p},i}) = u_{\mathrm{c}}(q_{\mathrm{m,p},i}) \cdot \frac{T_{\mathrm{int}}}{T_{\mathrm{e}}} = \sqrt{\sigma^2(q_{\mathrm{m},i}) + \left(u(q_{\mathrm{r},i}) \cdot \sqrt{\frac{T_{\mathrm{e}}}{T_0}}\right)^2} \cdot \frac{T_{\mathrm{int}}}{T_{\mathrm{e}}} \tag{2}$$

$$u(q_{\mathrm{env,d},i}) = u_{\mathrm{c}}(q_{\mathrm{m,d},i}) \cdot \frac{T_{\mathrm{e}}}{T_{\mathrm{int}}} = \sqrt{\sigma^2(q_{\mathrm{m},i}) + \left(u(q_{\mathrm{r},i}) \cdot \sqrt{\frac{T_{\mathrm{int}}}{T_0}}\right)^2} \cdot \frac{T_{\mathrm{e}}}{T_{\mathrm{int}}} \tag{3}$$

where $\sigma(q_{\mathrm{m},i})$ represents the standard deviation for each flow measurement station, and $u(q_{\mathrm{r},i})$ is the uncertainty of the flow measurement device (3% of the airflow reading).

Note that this methodology does not consider the systematic error due to the mathematical model error.

The general calculation procedure standard uncertainties $u_{\mathrm{c}}(n_{\mathrm{WLOC}})$ and $u_{\mathrm{c}}(\ln(C_{\mathrm{env,WLOC}}))$ for WLOC_1 and WLOC_2 is similar to what is proposed in (Delmotte, 2013).

Since the procedure for calculating the 95% confidence interval (CI) in ISO 9972 does not align with the GUM, the uncertainty calculation was adapted according to (Delmotte, 2013; Joint & Committee for Guides in Metrology, 2008), resulting in the OLS_2 method. Consequently, the CI of q_{ref} is computed using the expanded uncertainty U, which is derived by multiplying the combined standard uncertainty $u_{\mathrm{c}}(q_{\mathrm{ref}})$ with a coverage factor k:

$$CI(q_{\mathrm{ref}})_{\mathrm{GUM}} = q_{\mathrm{ref}} \pm U(q_{\mathrm{ref}}) = q_{\mathrm{ref}} \pm k \cdot u_{\mathrm{c}}(q_{\mathrm{ref}}) \tag{4}$$

It is a good choice to take $k = 2$ to define a CI of 95%. The combined standard uncertainty, $u_{\mathrm{c}}(q_{\mathrm{ref}})$, is calculated using the propagation of uncertainty principle (Joint & Committee for Guides in Metrology, 2008):

$$u_{\mathrm{c}}(q_{\mathrm{ref}}) = \sqrt{\begin{gathered}\left(\frac{\partial q_{\mathrm{ref}}}{\partial n} \cdot u_{\mathrm{c}}(n)\right)^2 + \left(\frac{\partial q_{\mathrm{ref}}}{\partial \ln(C_{\mathrm{env}})} \cdot u_{\mathrm{c}}(\ln(C_{\mathrm{env}}))\right)^2 + \\ 2 \cdot \frac{\partial q_{\mathrm{ref}}}{\partial n} \cdot \frac{\partial q_{\mathrm{ref}}}{\partial \ln(C_{\mathrm{env}})} \cdot u_{\mathrm{c}}(n) \cdot u_{\mathrm{c}}(\ln(C_{\mathrm{env}})) \cdot r(n, \ln(C_{\mathrm{env}}))\end{gathered}} \tag{5}$$

Unlike the equations outlined by Delmotte (Delmotte, 2013), we neglected uncertainties due to temperature measurements for simplification, assuming they have a minor influence on the final results. The third term in the equation represents the "correlation coefficient", reflecting the high correlation between the uncertainties on n and C_{env}.

2.3 Synthesis of regression techniques methodology

Figure 1 provides a schematic representation of the minimization criteria for each regression techniques (OLS, WLS, and WLOC). Table 1 details the procedure for calculating the confidence interval for these techniques.

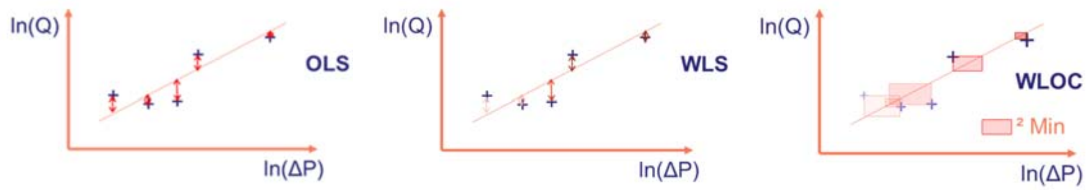

Figure 1: Schematic representation of regression techniques methodology for OLS, WLS, and WLOC

Table 2: Regression techniques and confidence interval calculation procedures

Procedures	OLS_1	OLS_2	WLS	WLOC_1	WLOC_2
Calculation of uncertainty on pressure difference and air flow rate measuring point	not considered	not considered	not considered	According to Delmotte and Prignon et al.	As proposed in this paper
Regression Technique	OLS	OLS	WLS	WLOC	WLOC
Calculation of uncertainty / confidence interval on the results	ISO 9972	In line with the GUM	Based on DIN EN ISO 9972	In line with the GUM	In line with the GUM

2.4 Dataset used for comparison

The data for this study was collected at the Alberta Home Heating Research Facility (AHHRF) in Edmonton, Alberta, Canada. This facility features six unoccupied test houses, each with unique construction. Detailed information about the facility and the dataset is available in Refs. (Walker et al., 2013; Wilson & Walker, 1993).

Each house underwent multiple measurements in various configurations, resulting in nearly 7,500 tests. These configurations varied due to different construction features like flue openings, sliding window states, or passive vent adjustments, leading to 127 distinct test scenarios. Each configuration involved between 5 and 140 tests, with 39% conducted in pressurization mode and 61% in depressurization mode.

This dataset underwent rigorous filtering to remove any missing or erroneous data. Additionally, the filtering process adhered to the following criteria set by ISO 9972:

- The absolute value of zero-flow pressure difference at the start and end of each test should not exceed 5 Pa.
- Each test must contain at least five data points, with the lowest data point being at least 10 Pa or five times the zero-flow pressure difference measured at the start. Some data points might be removed from a test to comply with this requirement.
- The highest pressure point in each test should be at least 50 Pa.

After this filtering process, the dataset was narrowed down to 6197 tests.
Pressure and airflow readings were collected at 15-second intervals.
A key aspect of our study was accounting for external environmental factors, such as varying wind conditions, on airtightness measurement results. Repeated measurements under diverse environmental settings provided a nuanced understanding of how such factors impact on building airtightness metrics. Meteorological, including outside temperatures ranging from -32 °C to +34 °C and wind speeds from close to $0\ \mathrm{m/s}$ to more than $10\ \mathrm{m/s}$, were recorded in parallel with each pressure/airflow reading.
Figure 2 demonstrated that the dataset includes tests conducted under challenging conditions (high wind), whilethe zero-flow pressure remains below 5Pa despite these conditions.

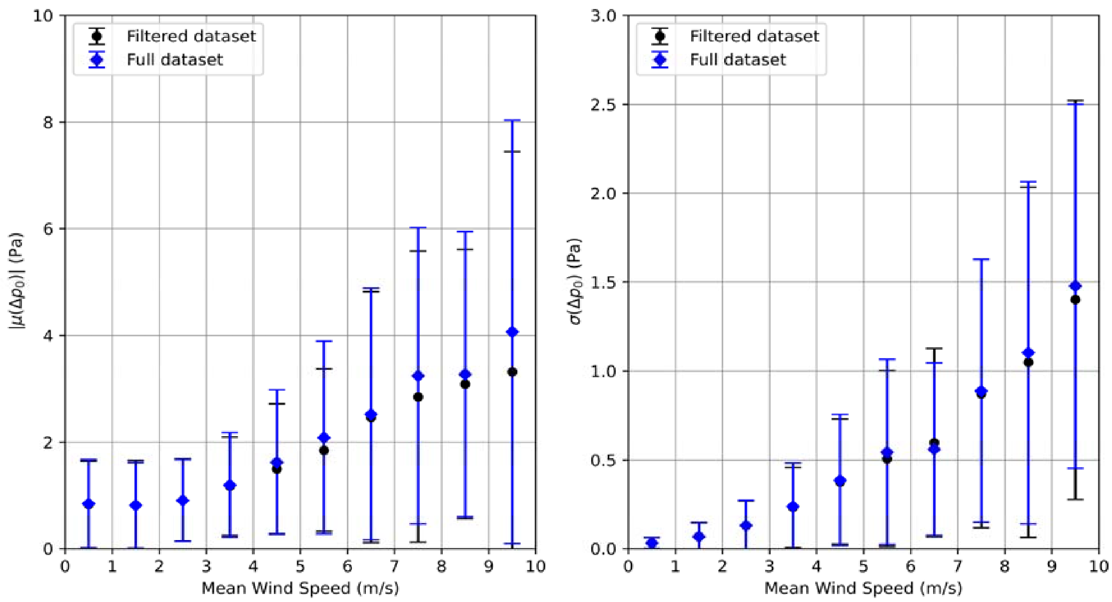

Figure 2: Distribution of mean absolute zero-flow pressure differences (left) and their respective fluctuations represented by the standard deviation (right) at increasing wind speeds in this dataset (black) and the full dataset (blue)

3 RESULTS AND DISCUSSION

3.1 Predictive capability

Figure 3 evaluates the efficacy of the five regression methods in predicting airflow at two distinct pressure differences: 50 Pa (q_{50}) on the left and 4 Pa (q_4) on the right side. The horizontal axis represents wind speed, ranging from 0 m/s to 10 m/s, while the vertical axis shows the Percentage Difference (PD) between the measured and the reference airflow values. Data points indicate the average PDs for measurements within each 1 m/s increment of wind speed.
Since OLS_2 employs the same regression method as OLS_1, their results overlap in the graphs. At 50 Pa, all regression methods demonstrate a similar ability to predict the reference airflow, with mean PDs not exceeding -6%, even at higher wind speeds. This consistency suggests that the choice of regression method minimally impacts the accuracy of airflow predictions at 50 Pa. Additionally, the error bars are similar across all regression method.
For both pressure differences, the mean PD remains around zero up to approximately 3 m/s, indicating that wind-induced errors do not introduce any bias at these lower wind speeds. Errors appear randomly distributed around zero, suggesting that other sources of random error are dominant. However, as wind speed increases beyond 3 m/s, a clear trend towards higher negative PDs emerges, particularly for q_4, highlighting wind as a dominant source of error. The

negative bias indicates an underestimation of the leakage flow rate due to the systematic error caused by the model that all leaks are considered as a single leak. At high wind speeds, the error is approximately 4 percentage points higher for OLS and WLOC_1 compared to WLS and WLOC_2 for q_4.

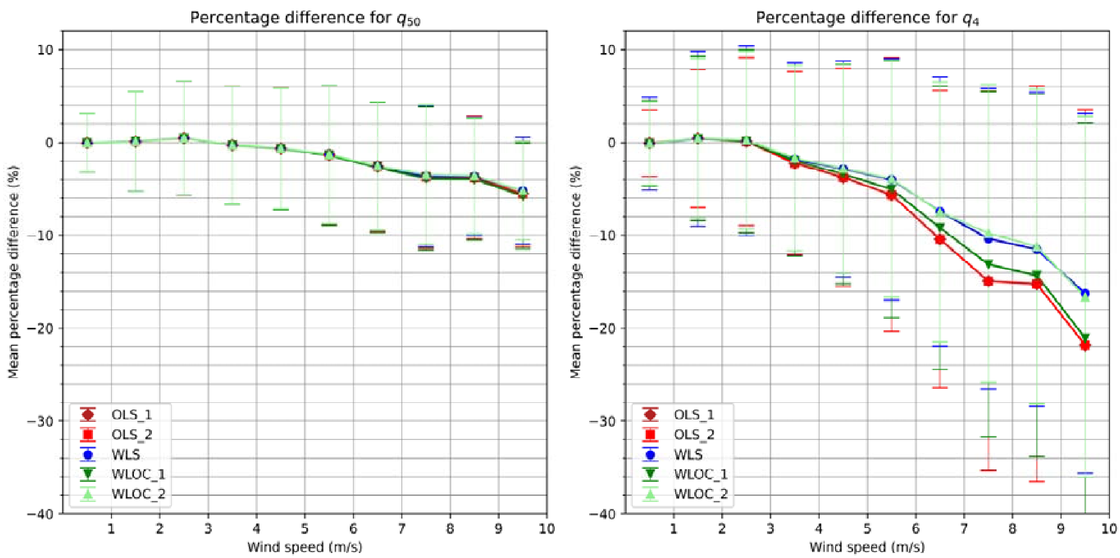

Figure 3: Mean values for increasing wind speeds of the percentage difference (PD) for calculated airflows at pressure differences of 50 Pa (left) and 4 Pa (right) and a reference value at these pressures with error bars representing the standard deviation

3.2 Uncertainty calculation relevance

Figure 4 illustrates the overall percentage of data points where the mean values of the calculated airflows at both 50 Pa and 4 Pa fall within the designated 95% confidence intervals, showing the relative performance of each regression method across the entire dataset.

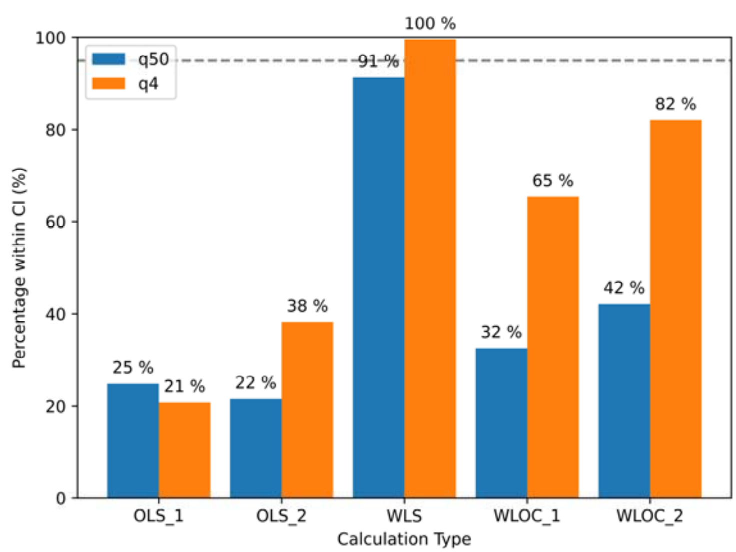

Figure 4: Total percentage per type of regression where mean values of calculated airflows at 50 Pa and 4 Pa fall into the 95% confidence interval

The WLS method demonstrates high overall coverage, achieving 91% for airflows at 50 Pa and full coverage at 4 Pa. Among the other regression techniques, WLOC_2 shows the best performance, maintaining coverage above 80% when extrapolating the flowrate at low pressure.

However, its effectiveness decreases when the calculating airflow at 50Pa, where coverage remains below 50%. This variation suggests that the method underestimate the actual uncertainty.

One reason the uncertainty calculation might fail to cover the 95% confidence interval is that not all sources of uncertainty are accounted for, and there is a systematic error that increases with wind speed, as shown in Figure 3. This error arises from the model itself. When correcting the data of this database for the average systematic error according to wind speed (Figure 3), the coverage changes only negligibly, not enough to alter the conclusion of this study. This systematic error depends on the distribution of leaks, which is unknown and cannot be corrected a priori. Although this error is systematic for a given building, it is effectively random because the exact leakage distribution in a given building cannot be known or controlled. An alternative approach could be to incorporate this model-induced error into the uncertainty calculation, which could be based on previous research (Carrié & Leprince, 2016; Delmotte, 2021).

4 CONCLUSIONS

This study presents a comprehensive evaluation of over 6,000 test series spanning 127 testing scenarios to assess the reliability and accuracy of three different regression analysis methods and different approaches for estimating measurement uncertainties in building airtightness measurements under varying climatic conditions. Our analysis particularly focuses on the influence of wind speeds on the results.

The findings reveal that the OLS and WLOC_1 regression methods seem slightly less effective in providing reliable airflow rates compared to WLS and WLOC_2, especially when the reference pressure is at 4 Pa and wind speeds exceed 4 m/s. A key observation is the systematic variation in measured air flow rates under different wind conditions. Data indicate that higher wind speeds consistently yield lower airflow rates than those measured under calmer conditions, highlighting the significant impact of wind on air leakage measurements.

Regarding error estimation, our analysis suggests that all methods, except WLS, tend to underestimate the actual uncertainty involved, which is consistent with expectations given that none of them can consider all sources of error. In contrast, the WLS method appears overly pessimistic at higher wind speeds and especially for lower pressures extrapolation, suggesting that in practice, pressure fluctuations may be less severe than predicted by this method. Wind speed variations are generally not as extreme, and the wind pressure coefficient on most building envelopes is significantly lower than 1. However, the procedure described in DIN EN ISO 9972 is not designed for calculating confidence intervals, and the method chosen in this paper is an attempt to approximate these intervals.

The WLOC_2 method seems to provide a notable improvement in error estimates over the OLS_1, as currently prescribed by ISO 9972, in particular at low pressure differences. However, there is still room for enhancement, particularly in integrating additional sources of error.

A limitation of this study lies in its relevance on real building configurations, where the 'true' values of airtightness are inherently unknown and can only be estimated under optimal conditions. Additionally, the study utilizes only a single building topology in the dataset. Future research could benefit from validating these findings under controlled laboratory settings, as suggested in (Mélois et al., 2024), to strengthen their applicability.

This study underscores significant implications for the standardization of building airtightness testing. We evaluated the performance of two standardized methods, OLS_1 and WLS, against three other methods that incorporate an improved uncertainty calculation procedure, including a simplified weighting scheme in the WLOC_2 method. Although the weighting procedure of WLOC could benefit from further refinement, the performances of the WLS and WLOC_2 regression methods suggest they should be considered for future inclusion in standards such as ISO 9972, given their respective advantages. However, the uncertainty estimation according to wind should be adapted for WLS. WLOC_2, with its valid uncertainty calculation procedure, and WLS both provide flexibility and enhanced reliability in testing procedures. Further investigation into the potential inclusion of the model-induced systematic error in the uncertainty calculation would be beneficial.

As we conclude, this study not only challenges existing methodologies but also paves the way developing more accurate and reliable airtightness testing standards. Adopting these advanced regression techniques and integrating comprehensive uncertainty calculations will be important for enhancing the predictive accuracy of airtightness tests.

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