Test of new analysis methodologies to assess dynamic airflow rate with the tracer gas decay method

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ABSTRACT

The measurement of natural airflows is practically challenging. Driving forces that induce natural airflows are characterized by low pressure differences. Conventional airflow-meters would introduce pressure drops, which can significantly affect the flow pattern. Besides, the measurement of the flow crossing a window is difficult to implement and poorly reliable. Thus, indirect methods called tracer gas methods are widely used to bypass these difficulties, as they do not interfere with the flow pattern. They rely on the analysis of the evolution of the concentration of a tracer gas, injected before or during the measurement.
However, tracer gas methods are subject to several uncertainty sources. To reduce the uncertainty due to concentration measurements, least squares regressions are often realised, which allow to smooth the measurement noise. If the regression is realised, airflows have to be stationary during the measurement, which is particularly questionable for natural airflows. Actually, for lack of better methods, these techniques are often used in natural conditions, assuming that the bias induced by the regression is inferior than the bias due to the measurement noise. The aim of the present paper is to experimentally assess a dynamic airflow rate with the commonly used multi-points tracer decay method, which theoretically assumes a constant ACH. The variation of airflows is realised thanks to a mechanical controllable fan, which allows a direct measurement of the airflow in the extract duct to test the accuracy of the tracer gas-dynamic ACH measurement.

KEYWORDS

Tracer decay method, Variable airflow, Kalman filter, Local least square regression.

1 INTRODUCTION

The measurement of natural airflow is a challenging task. Low pressure differences induced by the wind and buoyancy effects lead to an unstable flow path. An airflow-meter would introduce some pressure drops likely to interfere with the flow pattern. Tracer gas methods are the most widely used methods to assess natural airflows, as they do not interfere with the flow pattern. They provide the Air Change per Hour from the measurement of the emission rate and the concentration of the tracer gas. The three main tracer gas methods, that differ from the way of dosing the gas, are the constant concentration method, the constant dosing method, and the concentration decay method (Sherman, 1990). Among them, the concentration decay method is the most suited method to natural ventilation (Remion, 2019). One of the reason is that the artificial homogenization of the tracer gas, which is one prerequisite that may alter the flow path, can be realised before the measurement, contrary to other methods (AFNOR, 2017).

Analysing the decrease of the gas can come from the measurement of only two extreme points. The accuracy of this method is weak but it tolerates variable airflows. To increase the accuracy of the method, a least squares regression may be realised with several measurement points, leading to the multi-points decay method. However, the regression implies a stationary airflow assumption during the measurement, which is troublesome for natural ventilation systems. The aim of the present paper is to test two other analysis techniques that reduce the time laps of the assumed constant airflow, or even circumvent this requirement. The first technique is a moving least squares regression on a significantly reduced time laps. It is enabled by measurement instruments that allow now to have access to nearly continuous concentration data. The moving regression provides a dynamic ACH. The second technique is the use of a Kalman filter, which is a very convenient tool to reduce the measurement noise, while keeping the ability to track the parameter of interest, namely the dynamic ACH. Duarte et al. provide the mathematical development of the filter adapted to the Transient Mass Balance Equation metabolic CO_2 method (Duarte, 2018). Those methods will be compared to the 2 points decay method, which should be used when variable airflows are likely to occur (AFNOR 2017).

2 METHODS

2.1 Experimental setup

The test was conducted in an experimental cell of 2.45m width, 3.17m length and 2.65m height, leading to a volume of 20.6 m^3. The laboratory cell is featured with a controllable fan, allowing to simulate airflow variation profiles. An airflow-meter, which is installed in the extract duct connecting the fan to the room, provides the reference value of the airflow rate with an accuracy of 0.5%. Laussmann & Helm have proved the suitability of CO_2 by comparing tracer gas results from CO_2 and SF_6 (Laussmann, 2011). We chose CO_2 as a tracer gas during the experiment, considering that no internal sources were to take into account. We used two typologies of CO_2 sensors based on the NDIR[1] technology : two vaisala sensors with an accuracy of 4% and an acquisition frequency of 0.5 Hz, and five stand-alone C2AI sensors with an accuracy of +/- (50 ppm + 3%) with a frequency of one measurement every 12 sec. Table 1 presents technical specificities of measurement instruments. Two typologies of sensors were tested because stand-alone sensors are very convenient for in-situ applications, but their acquisition frequency and accuracy are weaker. The aim is to test the impact of the degradation of technical characteristics of sensors. Those sensors were averaged by types to inhibit the effect of imperfect mixing. Figure 1 presents a schematic of the experimental cell.

[1] Non Dispersive Infrared Technology

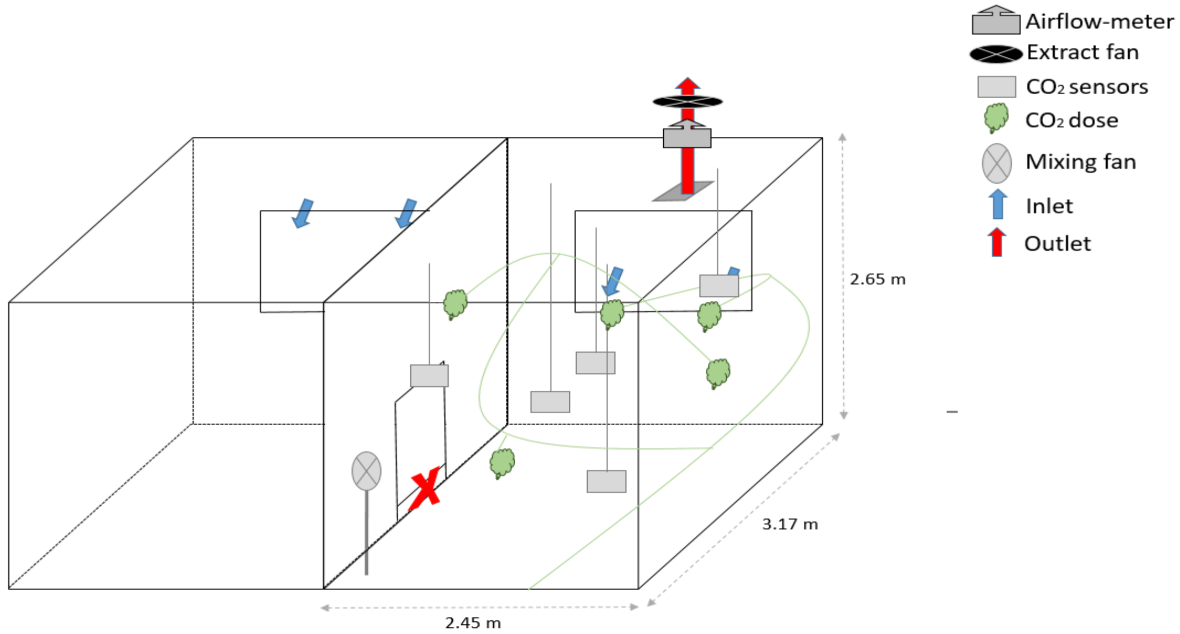


Figure 1 : Schematic of the experimental cell

Table 1: Instruments technical specificities

Measurement instrument	Technology	Accuracy	Acquisition frequency
C2AI CO_2 sensors	Stand-alone NDIR[1]	50 ppm + 3% reading	1/12 Hz
Vaisala CO_2 sensors	Wired NDIR[1]	4% reading	0.5 Hz
NZP Nozzle series airflow-meter	Pitot-tube	0.5% reading	0.5 Hz

2.2 Airflow variation profile

A mechanical ventilation system was used to reproduce airflows in accordance with airflows induced by natural conditions. We considered stack and cross ventilation. Stack ventilation was simulated by computing airflows from the formula characterizing the flow between two openings of different height (**equation 1**). The formula was filled with meteorological data measured by a local weather station in Lyon, France. Stack ventilation is mainly induced by buoyancy effects. In order to have significant fluctuations of airflow, we looked for a day with a significant temperature amplitude.

$$Q_{stack}(t) = C_d \, . A_{eff} \, . \sqrt{\frac{2 \, . \, g \, . \, \rho_{ext} \, . \, H \, . \, \frac{T_{ext} - T_{int}}{T_{int}}}{\rho_{int}}} \qquad (1)$$

With C_d [ ] the discharge coefficient, A_{eff} [m^2] the effective area, ρ_{ext} and ρ_{int} [kg.m^{-3}] the external and the internal density of the air, H [m] is the height between two openings, T_{ext} and T_{int} [°C] the external and internal temperatures, g [m.s^{-2}] the acceleration of gravity.

Airflows were then computed and two profiles were isolated, one in the morning leading to a monotonous decreasing profile [75 to 50 m^3.h^{-1} in 2 hours], and one in the afternoon, leading to a monotonous increasing profile [50 to 65 m^3.h^{-1} in 2 hours]. It corresponds to temperature fluctuations of 4°C in 2 hours. Those particular profiles were selected because it allows to have more than 5 air renewals in 2 hours (which is important for the constant dosing method) and because their mean values are similar.

To simulate a flow consistent with cross-ventilation, we used data from a study conducted by J. Lo et al. (Lo, 2012). They investigated the flow crossing windows of a multi-zone building. We determined two profiles from those data, based on a different multiplier coefficient (0.3 and 0.7). The coefficient 0.3 was chosen to set the mean airflow at the same level than the two aforementioned profiles. The coefficient 0.7 allows to test the impact of wider and faster fluctuations on the accuracy of tracer gas methods. Figure 2 shows airflows measured by the airflow meter, for each variation profile that have been used in the experiment.

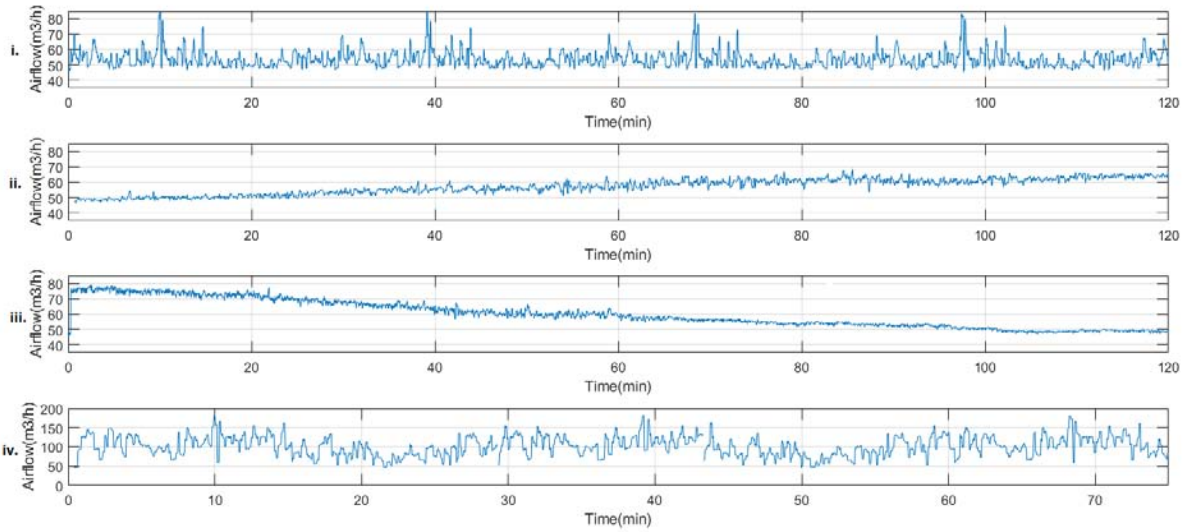


Figure 2 : Airflow variation profiles: (i) cross, (ii) stack increasing (up), (iii) stack decreasing (down), (iv) high cross (hicross)

2.3 Calculation of airflow

We will test three calculations of the airflow rate: the conventional 2 points decay formulation which is the standard-prescribed decay method in case of variable airflows, a local moving least squares regression that is to say a local moving multi-points decay method, and finally the Kalman filter. The formulation of the calculation of the 2 points decay ACH, and the multi-points decay ACH are given in Ref. (Roulet, 1991). For the local moving multi-points method, CO_2 concentrations were first smoothed thanks to a moving term average. A two minutes-time laps of both moving term average and moving multi-points method was arbitrarily chosen.

Concerning now the Extended Kalman filter, the mathematical development is available in Ref. (Duarte, 2018). The principle of the filter is to estimate the state parameter x (**equation 2**). Transition functions are defined to predict the value of the state parameter at the next time step (**equation 3**). Transition functions involve some process noise terms, that accounts for violations of assumptions of tracer gas methods. For instance, the process noise of the concentration (w_k^c) would be deviations from a perfect mixing of the fresh air, and process noise of the airflow (w_k^n) would be deviations from a stationary airflow. The prediction $\widehat{x_{k+1}}$ of the state parameter is then compared to the noise corrupted measurement (**equation 4**). The comparison provides the error (ε_{k+1}). The filter will finally update the estimation of the state parameter (x_{k+1}) from the calculated error by multiplying it by the Kalman gain, which is dependant on the Variance/Covariance matrix of the process noise (**W**) and the measurement noise (**V**). The measurement covariance matrix was defined in accordance with technical specificities of sensors. The covariance matrix of the process noise was set to: $= \begin{Bmatrix} 0.1\,ppm^2 & 0 \\ 0 & 0.001\,(Vol^2.h^{-2}) \end{Bmatrix}$. Added to the predicted state ($\widehat{x_{k+1}}$), it provides the updated state parameter. The block diagram of the filter is presented in Figure 3. A dynamic airflow rate is provided by successive states of the airflow rate n.

$$x_k = \begin{cases} C_k \\ n_k \end{cases} \tag{2}$$

$$\widehat{x_{k+1}} = \begin{cases} C_{k+1} = (C_k - C_{ext}) * e^{-n_k \cdot \Delta T} + C_{ext} + w_k^c \\ n_k = n_{k+1} + w_k^n \end{cases} \tag{3}$$

$$C_k^* = C_k + v_k^C \tag{4}$$

With C_k the concentration at time k [kg/kg], n_k the airflow rate at time k [Vol/h], C_k^* the noise corrupted measured concentration [kg/kg], ΔT the time laps between two measurements [h].

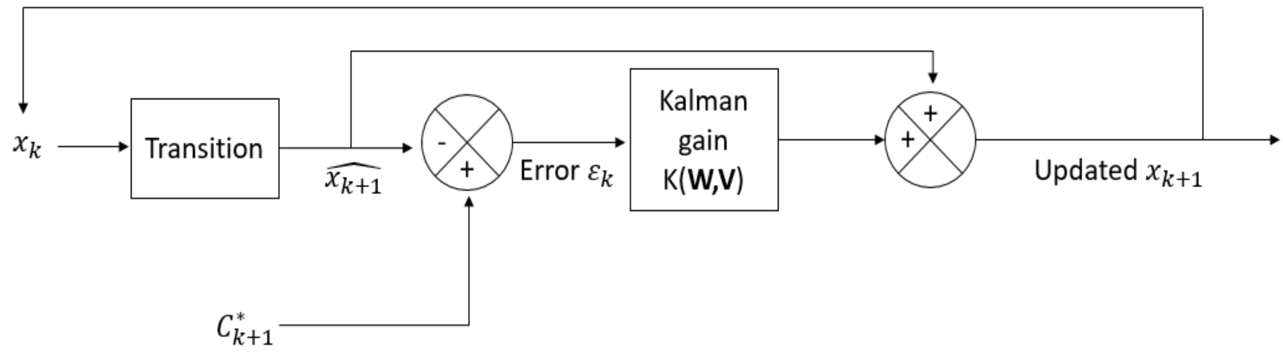


Figure 3 : schematic of the Extended Kalman filter principle

3 RESULTS

The mean airflow rate was computed with the 2 points method, and a dynamic airflow rate was provided by the Extended Kalman Filter and the Local fit methods. Figure 4 shows the evolution of dynamic airflows (Extended Kalman filter, Local fit) compared to the reference airflow measurement, performed by the airflow meter in the extract duct. The airflow profile which is showed is the most critical highly variating profile, consistent with cross ventilation. CO_2 concentrations used to compute airflows of Figure 3 come from wired Vaisala sensors with a good acquisition frequency (0.5 Hz). The time laps of the graph represents 2 air renewals. We can see that, apart from small fluctuations, both methods are very accurate, and account well for the dynamic airflow rate.

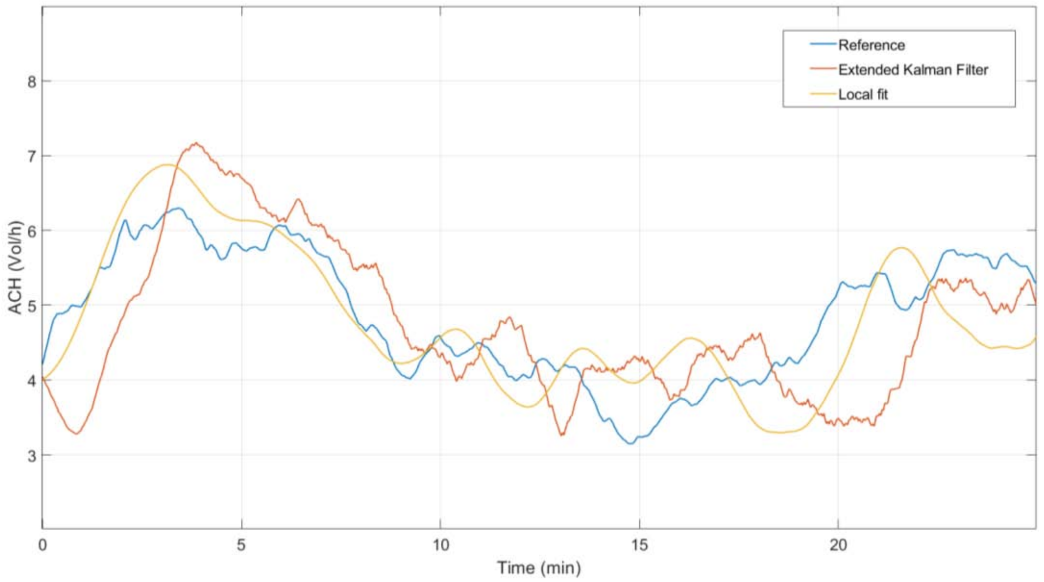
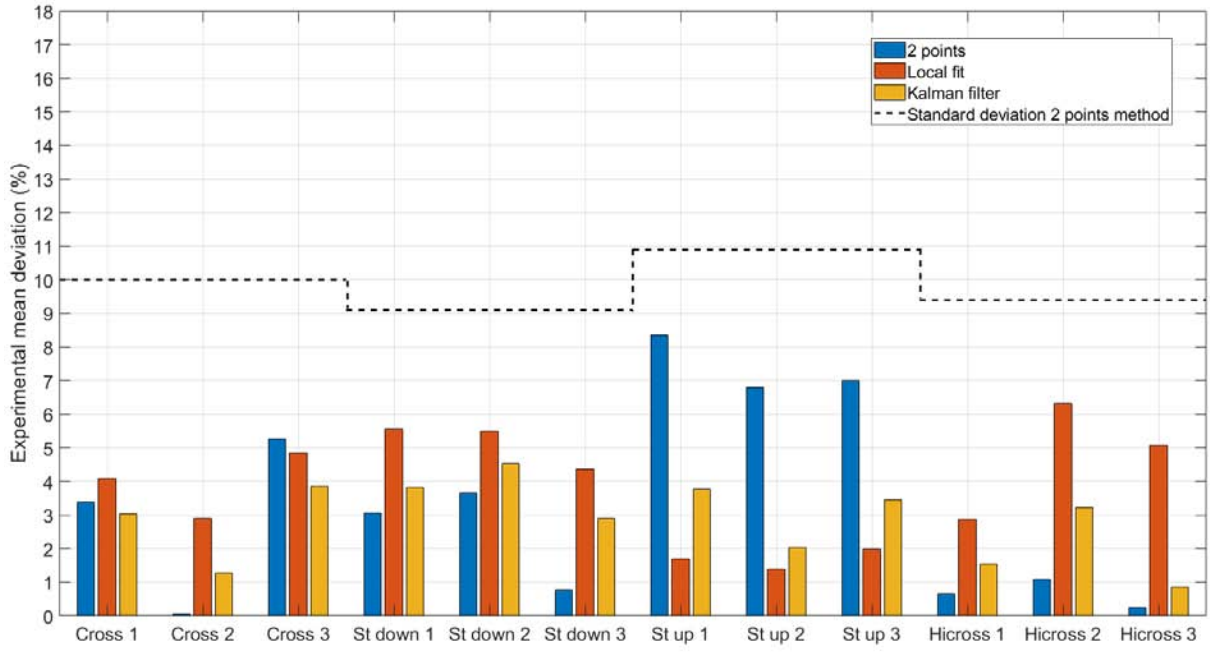


Figure 4 : Evolution of the reference airflow, and airflows calculated by the Extended Kalman filter and the local fit techniques, for the highly variating profile (Vaisala sensors)

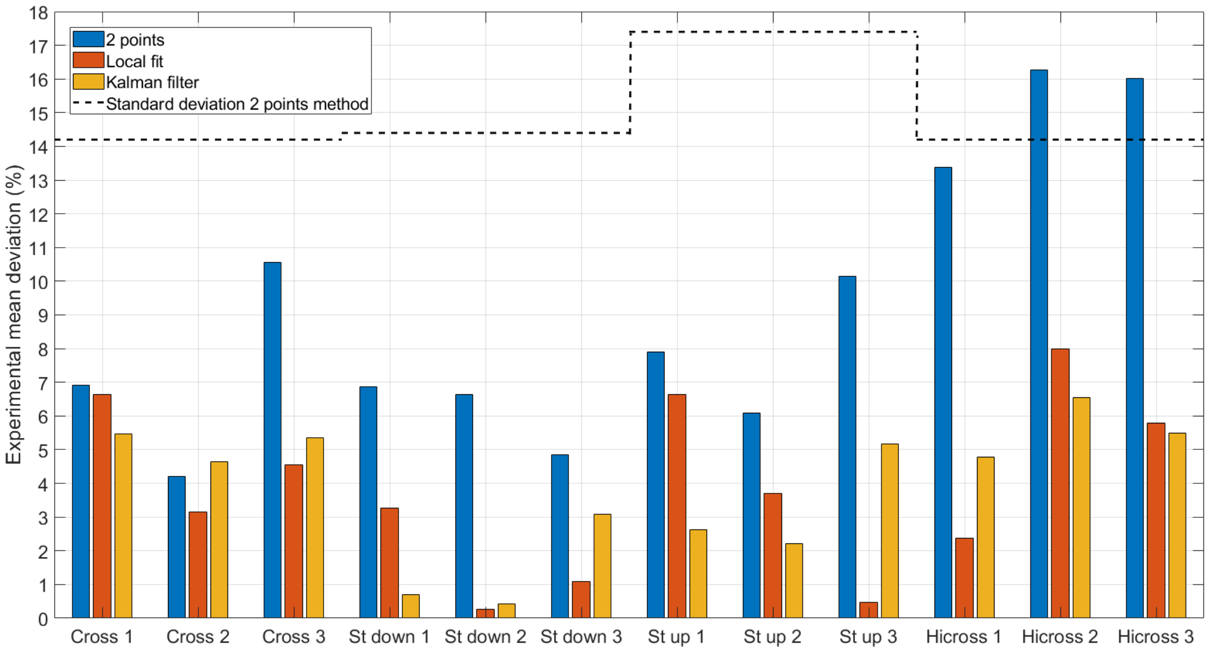
To compare the accuracy of the conventional 2 points method with others, we computed the average of the airflow rate from 5 minutes to the period allowing 2 air renewals for the three methods.

Figure 5 shows histograms of the Experimental mean deviation between methods and the reference value. Dash lines represent the standard deviation of the 2 points method, computed thanks to the error propagation law. The subplot (i) refers to stand-alone sensors (C2AI), and the subplot (ii) refers to wired sensors (Vaisala). For Vaisala sensors, apart from the stack increasing profile (St up), averaged deviations are far below the standard deviation. The Kalman filter and the local fit methods do not allow to significantly improve the accuracy, which is already very good. For the hicross profile, the local fit method leads to deviations from 1.5% (1.5 m^3/h) to 5% (5.1 m^3/h) higher than the 2 points method, whereas the Kalman filter leads to closer deviations (1% (1 m^3/h) to 2% (2 m^3/h) higher). However, the inverse conclusion occurs for the stack increasing profile: dynamic methods are between 4% (2.2 m^3/h) and 6.5% (3.6 m^3/h) more accurate. In general the Kalman filter leads to results between -5% (2.7 m^3/h) to +2% (1.1 m^3/h) against the 2 points method, while the local fit leads to results between -6% (3.3 m^3/h) to +5% (2.7 m^3/h). Also, the standard deviation between experimental deviations among each profile is lower for dynamic methods than for the 2 points method (2.5% against 3%), and so is the maximum mean deviation (6.3% (3.5 m^3/h) and 4.5% (2.5 m^3/h) against 8.5% (4.7 m^3/h)). Dynamic methods are more stable, with a slight advantage for the Kalman filter.

For C2AI sensors, a better accuracy of both dynamic methods is experienced for every experiment. The improvement of accuracy is significant for several experiment (3rd cross, 2nd down, 3rd up, every hicross experiments). Maximum mean deviations among profiles is about 6.5% (6.7 m^3/h) for the Kalman filter, 8% (8 m^3/h) for the local fit, and 16.3% (16.3 m^3/h) for the 2 points method. Standard deviations between experimental mean deviations among each profile is about 2.7% for the Kalman filter, 3.9% for the local fit method, and 4.2 % for the 2 points method. Once again, the Kalman filter leads to the lowest maximum deviation among each profile (6.5%), which occurred for the most critical highly variating profile, which varied around 5 Vol/h about +/- 20%.



(i)



(ii)

Figure 5 : Histograms of the experimental mean deviation for the three analysis techniques (i) Vaisala sensors, (ii) C2AI sensors

4 DISCUSSION

For wired sensors, the accuracy was not significantly improved compared to the conventional 2 points method, even if highest deviations between methods are in favour of dynamic methods. However, dynamic methods lead to more stable results among airflow profiles, as the standard deviation between each experiment are below than the one of the 2 points method.

Stand-alone sensors are more convenient for in-situ applications, but are often less accurate than wired sensors. This is an issue for the assessment of natural ventilation, because the 2 points decay method should be employed, whereas it is subject to significant measurement errors. The proposed dynamic methods allowed to significantly improve the accuracy, while allowing to track the evolution of the ACH. This is two significant assets to increase the reliability of tracer decay method in natural conditions. Leading to the same order of magnitude of the experimental error between the wired and stand-alone sensors, dynamic methods are less sensitive to measurement noise than the conventional 2 points method. Moreover, they seem not affected by the variation of airflows, contrary to the 2 points method. It remains some room for improvement as the process noise covariance matrix of the Kalman filter could be better characterized, and also the time laps of the moving local fit could be better chosen.

Among dynamic methods, the Kalman filter leads to slightly better results than the local fit. Moreover, no stationary airflows is assumed, whether the local fit assumes the airflow stationary during the time laps of the regression (two minutes here). The Kalman filter is theoretically speaking more adapted to natural ventilation's assessment.

5 CONCLUSION

Dynamic analysis methods of the well-known decay methods were tested under mechanical variable airflows, namely the Kalman filter, and the moving local least squares regression methods. Results are very encouraging as dynamic analysis methods allowed to significantly improve the accuracy, especially for stand-alone sensors, that are likely to be less accurate. They also allow to track the dynamic ACH, which is noteworthy for the tracer decay method.

These proposed analyses take advantage of the ease of implementation of the tracer decay method, while ensuring a relatively good accuracy if airflows are likely to fluctuate. The Kalman filter performed slightly better than the local fit, with deviations which are quasi-exclusively below 5%, with a maximum of 6.5% for stand-alone sensors with the hicross variation airflow profile.

6 ACKNOWLEDGEMENTS

We would like to thank the French ministry of ecology that funded this project. We would also like to thank Dr. James Lo, who provided experimental data necessary to create airflow variation profiles, consistent with cross ventilation.

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