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Development of a $PM_{2.5}$ Index Adapted to Short-Term Measurements to Provide Real Time Information to Residential Building Occupants

Mikaël Brunet, MD **Jérôme Nicolle, PhD** **Marc Abadie, PhD**

ABSTRACT

The ALLO project aims to be innovative in the way it approaches information and its dissemination to residents who are concerned about air quality in their home or are not familiar with the subject. In this paper, we are focusing on one important pollutant, i.e. $PM_{2.5}$*, on more particularly on low-cost sensors that provides* $PM_{2.5}$ *data in rooms at short timesteps (usually 5 min.). The* $PM_{2.5}$ *concentration level will be then analyzed and ad hoc recommendations will be given to the occupants according to the potential health hazards and the possibilities offered to them to improve their air quality. This paper aims to explore the relationship between* $PM_{2.5}$ *short-term concentrations and 24-hr averages used in exposure limit values or air index quality breakpoints that are related to the results of studies about the health impacts of air pollution. The goal is then to evaluate appropriate values for low, medium and high categories when using quasi real time* $PM_{2.5}$ *measurements. Data obtained by both in-situ measurements and numerical simulations are used to this extend. Preliminary results show that a moderate relationship between short-term and longer-term air quality data does exist and can be nevertheless employed to give adequate information about air quality to the residents.*

INTRODUCTION

The French ALLO project aims to be innovative in the way it approaches Indoor Air Quality (IAQ) and thermal comfort information and its dissemination to non-expert residents of social housing. Bringing together a team of scientists, technicians and sociologists, the project searches to contextualize the reception of interfaces such as tactile tablets and the understanding of data provided by sensors in the form of indices to encourage the change of behavior and in particular to provide easily understandable and feasible solutions within the home. It is a three-step project. First, a sociological study aimed at understand the domestic practices and the level of sensitivity to air quality. A second phase is dedicated to the development of the IAQ sensors, the analysis of measurement and the information to be given to the resident via a dedicated app. A post sociological study will evaluate the progress made since the first exchanges on

Mikaël Brunet is a research engineer at LaSIE (CNRS UMR 7356), University of La Rochelle, France. **Jérome Nicolle** is a research fellow at TIPEE platform, Lagord, France. **Marc Abadie** is an associate professor in the Department of Civil Engineering and researcher at LaSIE (CNRS UMR 7356), University of La Rochelle, France.

practices after 6 months of use of the tactile tablets distributed in the dwellings.

Besides environmental parameters such as temperature and relative humidity, the set of sensors will measure $PM_{2.5}$ concentration as a proxy to IAQ. The selection of $PM_{2.5}$ comes from both its importance in terms of health effects (and prevalence indoors) and the constraints of the present project. Firstly, $PM_{2.5}$ has been clearly identified as a pollutant of high priority in indoor environments. One can cite Kirchner et al. (2006), Hänninen and Knol (2011), Logue et al. (2011a, 2011b), ANSES (2014), Abadie and Wargocki (2017) and Cony Renaud Salis et al. (2017a). In all those indoor pollutant priorization studies, $PM_{2.5}$ is always in first position, far ahead of other pollutants (especially when DALY-scoring is used). Secondly, due to the specifications of the project, only one fixed location of the sensors is studied. In this way, it was decided to install the sensors in the daytime living space i.e. in the living-room/kitchen part of the apartments. As consequence, they will be particularly representation of indoor pollution due to indoor activities generating particles such as cooking, using candles, incense sticks or smoking, resuspension due to occupant displacements and coming from outdoor (outdoor air entering mostly via air inlet, infiltration and open windows in the living-room). Note that a TVOC sensor has also been added as a complementary information about air pollution from gaseous species but is not yet included in the IAQ evaluation.

This paper focuses on the definition of a dedicated $PM_{2.5}$ index for residential buildings. The key element here is the need of real time information to be delivered to the resident to enable actions to lower the $PM_{2.5}$ concentration i.e. to limit peaks of $PM_{2.5}$ concentration during occupant activities. As a compromise between the $PM_{2.5}$ sensor characteristics and the building management system (for data acquisition, analysis, storage and interaction with the residents), a 5 min timestep was defined. To our knowledge, IAQ index considering such a short duration does not exist as current IAQ indices were defined to evaluate long-term effects and are thus based on averaged pollutant concentration over a minimum of one representative week (Abadie and Wargocki 2017). The goal of the present study is to adapt an existent index for long-term exposure we developed for residential buildings (Cony Renaud Salis et al. 2017b) to short-term events. In a first part, we present the procedure and two sets of data (from on-site measurements and from simulations) we employed to this objective. The second part presents both the results of the analysis. The last part is dedicated to the discussion on the reliability of such procedure.

METHODOLOGY

Definition of the multi-pollutant index (for long-term exposure)

In a previous paper (Cony et al. 2019), we defined a multipollutant index called ULR-IAQ to evaluate long-term exposure of residents at home. It is based on the resident exposure (C), that is usually taken as the average concentration over one typical week or day, and long-term (LT) and short-term (ST) Exposure Limit Values (ELV) given by health authorities. Sub indices are calculated for each considered pollutant (p) as:

$$I_{ULR-IAQ,p} = 10 \times \frac{C_p - ELV_{LT,p}}{ELV_{ST,p} - ELV_{LT,p}} \tag{1}$$

The aggregated ULR-IAQ index is then calculated as the maximal value of the sub indices. ULR-IAQ is limited to a scale from 0 (good) to 10 (unhealthy). In the present study, we focused on $PM_{2.5}$ considering ELV_{LT} = 10 μg/m^3 (1 year) and ELV_{ST} = 25 μg/m^3 (24 h) as given by WHO (2006). Note that those values are for outdoor pollution. Outdoor particulate matter differs in terms of chemical nature and size distribution from the products of cooking, smoking… but, in the absence of dedicated values for indoor environments, they are the only existing exposure limit values.

Procedure to adapt ULR-IAQ $PM_{2.5}$ breakpoints to short-term responses

The methodology employed in the present study is based on the analysis of Mannshardt et al. (2017). As described in Figure 1, the purpose is to defined breakpoints adapted to short-term data (acquired every 5 min) from the original breakpoints relative to longer periods. Note that another approach would have been to used ELVs for shorter exposure but they are not available and only 24h and 1year ELVs do exist for $PM_{2.5}$ (WHO 2006). The objective is to obtain a similar distribution of concentration data according to the ten-level scale by considering the data at 5 min (with the adapted breakpoints) and at 24h (with the original ones). In a first phase, we used real data measured in three different homes to evaluate the breakpoints adapted to 5 min. Then, in a second phase, we produced a new set of data by simulation to test the validity of the new breakpoints. The next subsections present the main information regarding the experimental and numerical data employed here.

Figure 1 Schematic representation of the procedure (adapted from EPA 2016).

Experimental data

Table 1 presents the main characteristics of the three experimental campaigns noted 1 to 3. All measurements were made by Foobot devices with the exception of the first campaign where both the Foobot and BlueAIR devices were employed in the same home (#1). The three dwellings were located in the same city (La Rochelle, France) and differ in terms of geometry, occupancy and ventilation systems. Sensors are close to the kitchen for dwellings #1 and #3 (and thus subject to measuring cooking activities) whereas the sensor is far away from the kitchen for dwelling #2. Figure 2 (left graph) presents the concentration levels measured during these tests. We observe that those levels are similar showing that they mostly depend on the outdoor pollution than specific indoor sources. We also note that the BlueAir device tends to give higher (lower) maximum (minimum) but lower average/median concentration than the Foobot one. The higher concentration observed for #1F and #3F compared to #2F can be explained by the effect of cooking events that are only kept by the devices located in the kitchen vicinity. Figure 2 (right graph) presents the data distribution using the original ULR-IAQ breakpoints. Most of the data are in the first interval (ULR-IAQ=1) or in the first half of the scale (ULR-IAQ<5). Almost no data can be seen in the highest intervals except for the last one (ULR-IAQ=10).

Table 1. Experimental data

#	Dwelling	Occupancy	Sensor	Sensor location	Ventilation	Period of time
1B	2-storey house	2 adults/1 child	BlueAIR	Kitchen/dining-room	Exhaust (old)	11/21/19 - 02/28/20
1F	2-storey house	2 adults/1 child	Foobot	Kitchen/dining-room	Exhaust (old)	11/21/19 - 02/28/20
2F	1-storey house	2 adults	Foobot	Living-room (separated kitchen)	Natural	12/23/19 - 02/29/20

3F	Studio	1 adult	Foobot	Kitchen/dining-room	Exhaust (new)	01/14/20 - 02/28/20

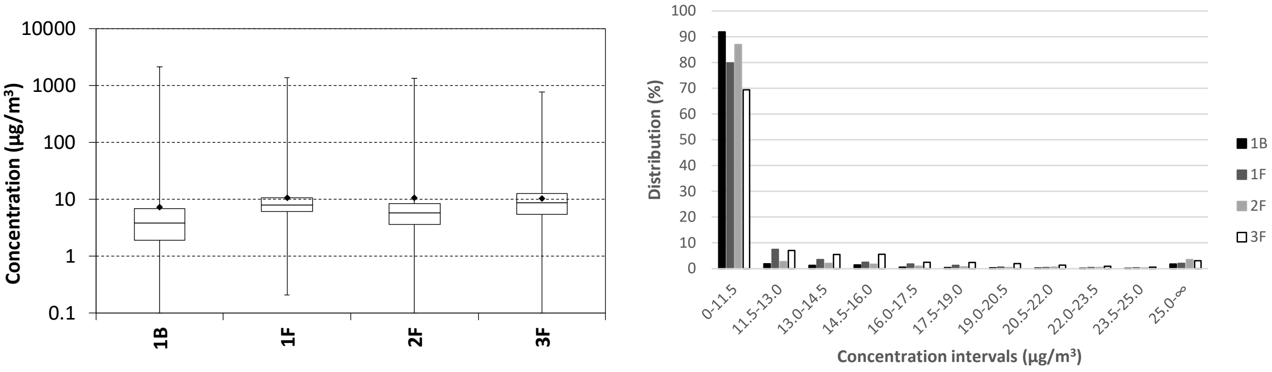

Figure 2 $PM_{2.5}$ concentration levels for the experimental data (left: statistics; right: distribution according to original ULR-IAQ breakpoints).

Numerical data

We defined a two-story house with 3 bedrooms and a bathroom upstairs and a living-room and a kitchen on the first level. This building geometry and furnishing surfaces, as well as heat and moisture sources, were not modified in this study. Simulations have been performed for two consecutive winter weeks using the coupling procedure of TRNSYS and CONTAM softwares (Cony Renaud Salis et al. 2018). The parameters that have been considered are presented in Table 2. Simulations 1S and 2S are identical except for the outdoor pollution. Bordeaux is a city slightly more polluted (in terms of $PM_{2.5}$ concentration) than La Rochelle. Simulations 1S (2S) and 3S (4S) are identical except for the presence of a smoker in the living-room in the evening. $PM_{2.5}$ concentrations have been saved every 5 min to mimic the data obtained by an IAQ device located in the living-room. The living-room concentration levels for the numerical data are presented in Figure 3 (left graph). Unsurprisingly, we observe lower concentration levels for La Rochelle compared to Bordeaux and slight increases due to the smoking activity in both cases. Moreover, the results of simulation 1S can be compared with the measurements from Figure 2 that have been held in the same city, without smoking activity. First, the levels are slightly higher in the simulation but remain about 10 µg/m³. Secondly, the main difference lies in the extrema whose are much higher in the real houses than those obtained by simulation. This essentially comes from the fact that the real sensors measure in one location and are subjected to local pollution (and local peaks, either maximum and minimum) whereas the results of simulation are averaged within the room as it is based on the well-mixed assumption (the concentration is the same within the indoor space). Figure 3 (right graph) presents a distribution more equally distributed with once again more data in the first interval (ULR-IAQ=1) and in the last one (ULR-IAQ=10).

Table 2. Simulation data

#	City	Sensor location	Specification
1S	La Rochelle	Living-room	Cooking activity at 12 a.m. and 7 p.m.; windows opening in the evening
2S	Bordeaux	Living-room	Cooking activity at 12 a.m. and 7 p.m.; windows opening in the evening
3S	La Rochelle	Living-room	In addition to the 1S, the occupant smokes a cigarette in the living room between 6 p.m. and 9 p.m.
4S	Bordeaux	Living-room	In addition to the 2S, the occupant smokes a cigarette in the living room between 6 p.m. and 9 p.m.

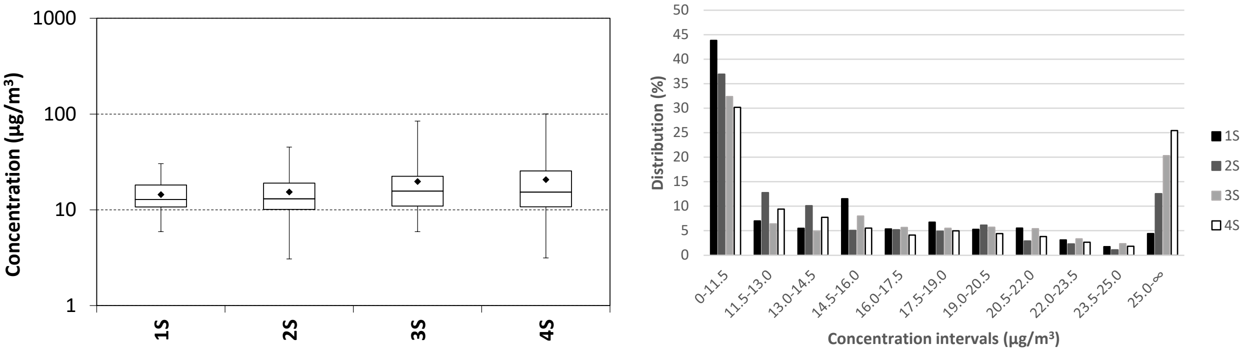

Figure 3 $PM_{2.5}$ concentration levels for the numerical data (left: statistics; right: distribution according to original ULR-IAQ $PM_{2.5}$ breakpoints).

RESULTS AND DISCUSSION

Using the original ULR-IAQ $PM_{2.5}$ breakpoints

Figure 4 presents the distribution of the experimental (left) and numerical (right) data according to the original ULR-IAQ breakpoints (see Figure 1, upper graph for values). All data, i.e. all data collected in-situ and from the 4 simulations, have been used to produce these two graphs. In particular, using the same breakpoints with 5 min data leads to an overestimation of 5.4% of the time with very good air quality using the experimental data and 16.6% with the numerical ones.

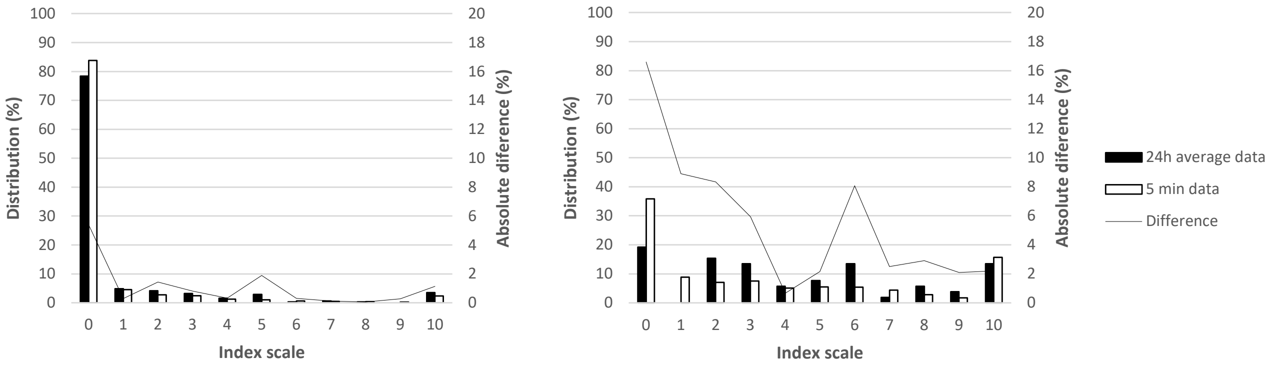

Figure 4 Distributions of daily-averaged and 5 min data considering the original breakpoints (left: experimental data; right: numerical data).

Adapting the ULR-IAQ $PM_{2.5}$ breakpoints to 5 min timestep

Figure 5 presents the distribution of the experimental (left) and numerical (right) data according to the adapted ULR-IAQ breakpoints. Again, all have been used to produce these two graphs. The difference here lies in the breakpoints used to calculate the distribution of the 5 min data. These breakpoints have been fitted starting with the lowest value to minimize the distribution difference between the daily-averaged (using the original scale) and the 5 min data. It is important to notice that, as presented in Figure 1, the breakpoint includes only one decimal as it does not make sense to have more precise value in terms of $PM_{2.5}$ concentration. As a consequence, the breakpoints are modified by 0.1 µg/m³ step to minimize the difference and so no perfect results can be achieved. That can be observed in the graphs where the maximal absolute difference of 0.11% for the experimental data and 1.35% for the numerical ones is obtained. The higher difference when using the data from simulation can be explained by the lower number of data (14 980 compared to 92 525 for the experiments) and by the almost constant $PM_{2.5}$ concentration evolution as only the outdoor concentration was variable (the other $PM_{2.5}$ sources being kept constant with unmodified schedules).

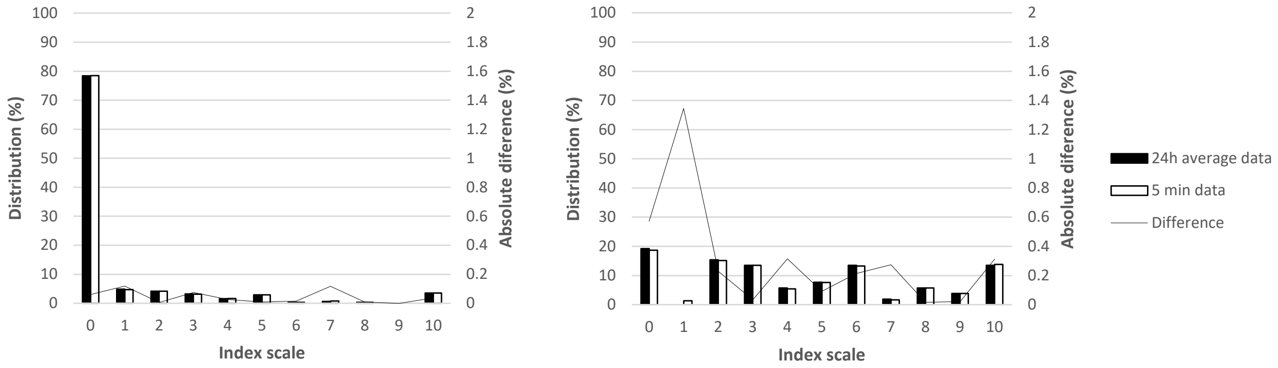

Figure 5 Distributions of daily-averaged considering the original breakpoints and 5 min data considering the fitted breakpoints (left: experimental data; right: numerical data).

ULR-IAQ $PM_{2.5}$ breakpoints for long and short-term data

Table 2 presents the ULR-IAQ original breakpoints (Long-term BP) along with those for a short period of 5 min based on the experiment and simulation datasets. Class 1 breakpoints are not so different among the cases so it may be concluded that using the original breakpoints would have no real impact on the detection of "good air quality". However, the upper classes (index > 5) that correspond to polluted air are quite different especially with the ones calculated using the experimental data that is the most reliable one. In this case, much lower episodes of "bad air quality" would be detected using the original breakpoints with 5 min data.

Table 2. Comparison between long- and short- term breakpoints (µg/m³)

ULR – IAQ Index	Long-term BP	Short-term BP EXPERIMENT	Short-term BP SIMULATION
1	< 11.5	< 10.0	< 10.5
2	11.0 – 13.0	10.0 – 11.3	10.5 – 10.6
3	13.0 – 14.5	11.3 – 12.7	10.6 – 11.7
4	14.5 – 16.0	12.7 – 14.1	11.7 – 14.2
5	16.0 – 17.5	14.1 – 15.1	14.2 – 15.3
6	17.5 – 19.0	15.1 – 17.8	15.3 – 16.9
	19.0 – 20.5	17.8 – 18.5	16.9 – 21.0
7	20.5 – 22.0	18.5 – 19.7	21.0 – 21.5
8	22.0 – 23.5	19.7 – 20.5	21.5 – 23.9
9	23.5 – 25.0	20.5 – 20.6	23.9 – 27.6
10	≥ 25.0	≥ 20.6	≥ 27.6

CONCLUSION

The present study aims to adapt an existent $PM_{2.5}$ index for long-term exposure we defined for residential buildings to short-term events. The methodology employed here was to recalculate the $PM_{2.5}$ breakpoints to match the distribution according to the 10-degree scale. The results show that the $PM_{2.5}$ breakpoints have to be adapted when using this index with data acquired with shorter timesteps. One perspective to this work is to compile more data. In particular, we want to generate much more data from simulation with variable parameters to complete/refine the present approach which was a preliminary numerical analysis.

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NOMENCLATURE

BP = Breakpoints
C = Concentration
DALY = Disability-Adjusted Life Years
ELV = Exposure Limit Value
IAQ = Indoor Air Quality
ST = Short-Term
LT = Long-Term
TVOC = Total Volatile Organic Compounds

Subscripts

p = pollutant

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