A Low-Cost Sensors Study Measuring Exposure to Particulate Matter in Mobility Situations

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Abstract: In 2013, the International Agency for Research on Cancer classified particulate matter (PM) as carcinogenic to humans. It is therefore essential to measure PM concentrations to minimize the exposure of individuals. Our objective was to investigate personal exposure to $PM_{2.5}$ (PM with diameter ≤ 2.5 µm) in Grenoble (France) during commuting in different transportation modes: bike, walk, bus and tramway. $PM_{2.5}$ measurements were found to be the highest for bikes, followed by walk, bus, and tramway. In this study, conducted in spring during low pollution levels of PM, exposure levels are greatly influenced by the time of day. Pedestrian and cyclists' exposure generally stayed under background reference values. Exposure in public transportation was usually below reference values, but when background $PM_{2.5}$ levels went lower (evening), levels registered in the tramway or bus reached those of the reference. Therefore, public transport users could be less exposed than active commuters, except when ambient pollutant levels are low. Environmental parameters like wind might be important in Grenoble, and it would be worthwhile to reproduce this study at a time when wind speed is lower.

1 INTRODUCTION

Every year, it is estimated that outdoor air pollution causes 7 million deaths around the world (Fuller et al., 2022). Particulate matter (PM) is made of solid compounds suspended in the air that are small enough to be inhaled. Considered as the most dangerous form of air pollution, PM can enter blood circulation, and accumulate in numerous organs (Pryor, Cowley, & Simonds, 2022). Therefore, it is important to assess populations' exposure to PM, which is generally done by official reference monitoring stations. However, more and more scientists state that stationary monitoring stations are not always representative of people's exposure (Van den Bossche et al., 2015; F. Yang et al., 2019). This might be related to the time that people spend indoor and outdoor, in places where the pollutant levels do not always equal to reference values. Time spent in transportation could represent up to 30% of the inhaled dose (Dons, Int Panis, Van Poppel, Theunis, & Wets, 2012). According to Han et al. (2021), personal exposure to $PM_{2.5}$ (PM with diameter ≤ 2.5 µm) measured by portable sensors, is significantly associated with an increase in respiratory and systemic inflammatory biomarkers. However, the associations are weaker when ambient $PM_{2.5}$ concentrations, measured by fixed reference stations, are used as an exposure proxy. Low-cost sensors demonstrate good accuracy to measure individual exposure to PM (Motlagh et al., 2021) and can therefore be used for exposure studies, especially during commuting. Few mobility studies involving low-cost sensors have been performed, especially in low-concentration situations. Many surveys take place in Asia where pollution levels are usually higher than in Europe. During 10 working days, we conducted a field experiment to collect PM measurements using four transportation modes around Grenoble (France): bike, walk, bus, and tramway. Our objective was to estimate personal exposures to $PM_{2.5}$ with a low-cost sensor during commuting in different modes. Another purpose was to compare the so measured concentrations with reference values. We wanted to know whether the low-cost sensors could be used to assess differences between transport modes and the time of day. In

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doing this, we hope to contribute to the exposure literature using low-cost sensors.

2 MATERIALS AND METHODS

2.1 Particulate Matter Sensor

2.1.1 Monitoring Devices

PM concentrations were measured using two AirBeam2 (HabitatMap), which entail an optical sensor (Plantower PMS7003). AirBeam2 are inexpensive ($249) and measure concentrations of PM_1, $PM_{2.5}$, PM_{10}, temperature and relative humidity (RH). They are connected to a smartphone via Bluetooth and provide real time values to users. With the growth of the Internet of Things (IoT) sector (Das, Ghosh, Chatterjee, & De, 2022; Y. Yang et al., 2022), cheaper PM sensors are currently available on the market. However, they often have to be assembled with other components like microcontrollers or GPS modules, and an IoT platform has to be set-up for data visualisation. Designing a monitoring station, assembling components and developing a data visualisation tool are different steps which can be time-consuming. HabitatMap already provides an online platform (http://aircasting.org) for viewing and downloading AirBeam2 data. Furthermore, AirBeam2 are ready-to-use devices. South Coast Air Quality Management District (2018) compared the AirBeam2 $PM_{2.5}$ measurements to values given by three Federal Equivalent Method instruments. They observed very strong correlations in the laboratory studies (R^2 > 0.99) and moderate to strong correlations with different reference instruments from the field ($0.68 < R^2 < 0.79$). More recently, Tong, Shi, Shi, and Zhang (2022) found that Airbeam2 measurements correlated well with roadside official monitoring stations. They also reported a good agreement ($R^2 = 0.67$–0.89) between Airbeam2 local measurements and the predictions from a model involving satellite observations. AirBeam2 is already calibrated by the manufacturer, but the calibration equations do not account for RH (HabitatMap, 2022). Huang et al. (2022) found that the accuracy and bias of the PM data reported by AirBeam2 sensors were affected by rainy weather and high humidity environments. Moreover, Zou, Clark, and May (2021) suggested that there was a significant linear relationship between RH and the relative response of the low-cost PM sensors to the research-grade instruments. Therefore, we calibrated the devices by accounting for RH.

2.1.2 Calibration

The calibration process involved two steps (Figure 1).

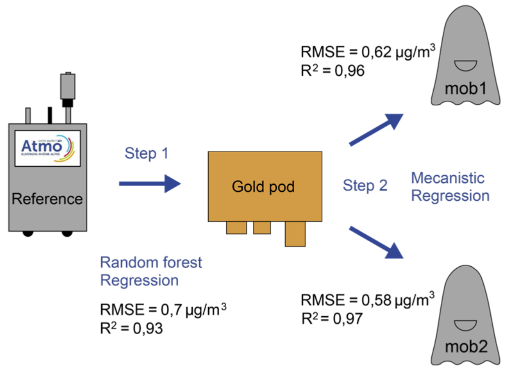

Figure 1: Two steps calibration process.

- **Step 1: Calibration of a Fixed Low-Cost Sensor ("Gold Pod") with a Reference Device**

Before this study, we had already calibrated a low-cost fixed station by collocating it with a Palas GmbH 200 (Reference) from Atmo Auvergne-Rhône-Alpes (Atmo AuRA) in Grenoble "Les Frênes" (Refer Figure 4). This calibration was performed using a random forest regression technique developed by Schmitz et al. (2021) comparing this individual fixed sensor with the reference station. This low-cost fixed station, called "gold pod" used the same optical sensor (PMS7003) than the mobile devices.

- **Step 2: AirBeam2 Sensors Calibration with a Fixed Low-Cost sensor ("gold Pod")**

Next, 44 days of calibration were performed from September 20, 2022 to November 3, 2022 where the two AirBeam2 were collocated close to the "gold pod". The two mobile devices were calibrated independently: first, the AirBeam2 used by experimenter 1 ("mob1") and then the device used by experimenter 2 ("mob2"). This was motivated by the observation that mob2 was delivering concentrations a bit higher than mob1. By using the nls() function from RStudio 2022.07.1 (R Core Team, 2022) on 75% of the dataset, we applied the mechanistic equation (Equation 1) involving relative humidity and temperature for calibration:

$$PM_{2.5\ gp} = a + b\,\frac{PM_{2.5\ mob}}{\left(1+d\,\frac{RH_{mob}}{100-RH_{mob}}\right)^{\frac{1}{3}}} + c\,T_{mob} \quad (1)$$

where $PM_{2.5\ gp}$ = $PM_{2.5}$ concentrations in µg/m³ given by the "gold pod", $PM_{2.5\ mob}$ = $PM_{2.5}$ concentrations (µg/m³) measured with the AirBeam2, RH_{mob} = relative humidity in % determined by the AirBeam2, T_{mob} = temperature in °C given by the AirBeam2. For mob1, we found a = 0.49, b = 0.91, c = 0.07 and d = 0.43. For mob2, we had a = -0.1, b = 0.86, c = 0.08 and d = 0.31. We then tested these two calibration formulas on the remaining 25% dataset, and we found the following performance indicators. For mob1, we had RMSE = 0.62 µg/m^3 and R^2 = 0.96 and for mob2, we found RMSE = 0.58 µg/m^3 and R^2 = 0.97. RMSE (root mean square error) reflects the accuracy of the model to predict actual $PM_{2.5}$ values, and R^2 (coefficient of determination) refers to the correlation between the AirBeam2 values and the reference concentrations. Based on this, we decided to continue with these models as the indicators were good compared to what is found in the literature (Blanco et al., 2022; Haghbayan & Tashayo, 2021).

2.2 Sampling Design

2.2.1 Monitoring Routes

The study took place in Grenoble, the largest city in the Alps, hosting around 450,000 inhabitants. Five different monitoring sites were selected (Figure 2): two wide streets ("Jaurès" and "Pain") and two narrow (also called "canyon") streets surrounded by higher buildings ("Grégoire" and "Blanchard"). We also monitored PM when we commuted between Blanchard and Grégoire ("Cross" route).

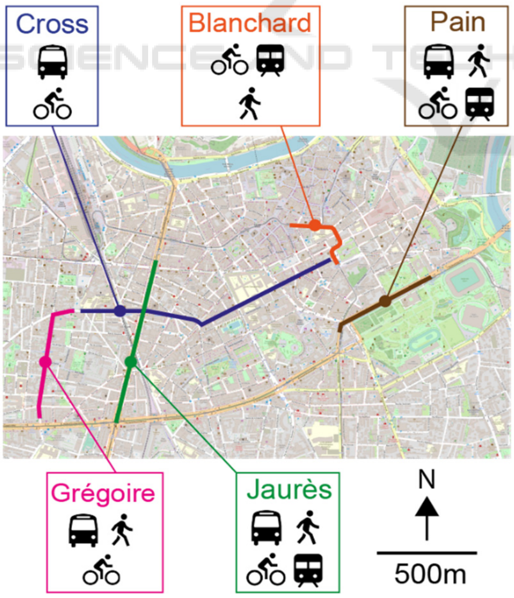

Figure 2: Monitoring routes used in the experiment. Credits: © OpenStreetMap contributors.

2.2.2 Experimental Timings

Ground measurements were conducted from April 25, 2022 to May 12, 2022 during 10 working days (Figure 3). Three different measurement sessions were performed daily: a first session (S1, morning) between 8:00 and 9:00, a second session (S2, noontime) between 12:00 and 13:00 and a third session (S3, afternoon) between 16:00 and 17:00. Sometimes, for reasons related to the public transport timetables, the sessions went slightly beyond the time slots. Nine sessions were postponed because of rainy conditions.

Two experimenters were involved in the study. For each session, they had to travel the same routes in parallel using different modes of transport: bike, walk, bus or tramway (Appendix). Each site was sampled for at least three days (Figure 3). On the days when we studied Blanchard and Grégoire, we also monitored PM while travelling in between the two sites ("Cross" route). Jaurès was sampled four times because this street, longer than the others, had many potential biases (intersections, stores, idling cars) and we thought it might be interesting to replicate the measurements further.

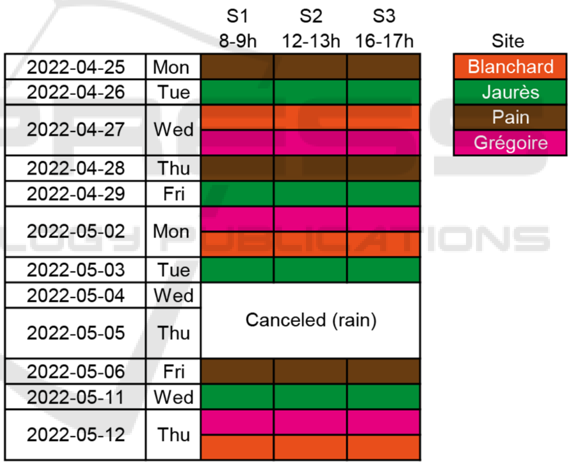

Figure 3: Measurement campaign schedule.

Next, we analysed carefully the public transportation schedules. A session example is reported in the Appendix. The same document was used as a roadmap by the experimenters for each session. Reproducing measurements on the same street is important to be representative (Van den Bossche et al., 2015). Every day, each experimenter performed at least 12 repetitions of the route.

2.3 Data Cleaning

In this paper, we decided to focus only on $PM_{2.5}$ analysis and on commuting times. We left PM_{10}, PM_1, and results related to waiting times for further work.

Data were extracted via AirCasting application and analysed with RStudio. We retrieved 214 comparison trips where the two experimenters were travelling along the same routes (428 trips in total, considering both experimenters). PM sensors can be vulnerable to inaccuracies resulting from drift, temperature, humidity and other factors (Motlagh et al., 2021). As both AirBeam2 were quite new, drift was not an issue, but we blew compressed air through the intake of the gold pod used for calibration as recommended by Bathory, Dobo, Garami, Palotas, and Toth (2021). As explained above, both AirBeam2 devices were calibrated using formulas accounting for RH and temperature. We also checked the presence of dust with CAMS (Copernicus Atmosphere Monitoring Service) satellite data (retrieved 0.1° x 0.1° resolution dust values from ENSEMBLE dataset (METEO FRANCE, 2020) ('analysis' type)). Fortunately, no dust event happened during the experiment period. We removed outliers in the dataset because we had peak events on trips, even inside public transports, mainly because of smokers or idling cars. In public transports, those peaks were often caused by door openings. All outliers with more than 1.5 times the interquartile range above the third quartile (Q3) or less than 1.5 times the interquartile range below the first quartile (Q1) were removed. Hourly background reference $PM_{2.5}$ concentrations from Atmo AuRA were collected through their Application Programming Interface (https://api.atmo-aura.fr/). For this study, we used the average from two background reference stations (Les Frênes and Saint-Martin d'Hères). Both references, placed at approximately 3 km from the experimental sites, were located in relatively open areas (Figure 4). For each measurement made every second with our mobile devices, we affected the corresponding hourly value

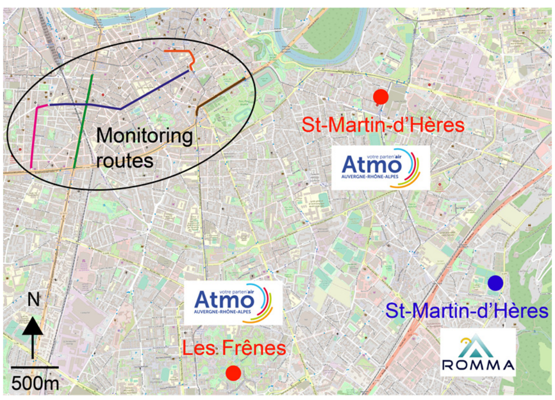

Figure 4: Location of the Atmo AuRA reference stations (in red) and ROMMA meteorological station (in blue). Credits: © OpenStreetMap contributors.

given by the reference stations. We also used meteorological data from the Réseau d'Observation Météo du Massif Alpin (ROMMA, 2022). Their nearest weather station (GPS coordinates: latitude = 45.169°, longitude = 5.768°) was located around 3 km from the collocation site (Figure 4). A Davis Vantage Pro2 instrument registered all weather parameters. Wind speed (km/h) corresponded to a 10-mn average, with a measurement frequency of 2.5-3 s. We checked that all data sources used the same time zone (Europe/Paris).

3 RESULTS

3.1 Descriptive Statistics

Collected $PM_{2.5}$ data are summarized in Table 1. More measurements were performed on walking mode because, in order to replicate the experiment and use public transportation again, we had to walk back to the starting point. This was especially true on routes where public transport was only running in one direction. The number of measurements made on foot were also higher because walking the road segment took longer than cycling, taking the bus or tramway.

Table 1: Descriptive statistics on $PM_{2.5}$ concentrations and number of measurements (count) performed in different commuting modes.

Dataset with outliers

		$PM_{2.5}$ (µg/m³)			
mode	count	median	SD	min	max
Bike	21448	8.21	2.33	3.04	35.46
Walk	73438	8.03	3.10	2.34	79.99
Bus	23374	7.44	2.05	2.30	26.44
Tram	14592	7.16	1.71	2.69	18.03

Dataset without outliers

		$PM_{2.5}$ (µg/m³)			
mode	count	median	SD	min	max
Bike	20451	8.08	1.94	3.04	17.50
Walk	69570	7.88	1.81	2.34	16.91
Bus	22638	7.37	1.97	2.30	18.97
Tram	13990	7.08	1.65	2.69	12.98

More outliers were identified for walking (5.3%) than for cycling (4.6%), tramway (4.1%) or bus (3.1%). Walkers are generally more exposed to PM coming from smokers, restaurants or bakeries. In addition, they are close to idling cars. When leaving outliers in the dataset, cyclists were more exposed (median: 8.2 µg/m³) than walkers (median: 8 µg/m³), followed by buses (median: 7.4 µg/m³) and tramway (median: 7.2 µg/m³). Compared with cyclists, pedestrians were 2.2% less exposed, bus users 9.4% less and tramway commuters 12.8% less. When removing outliers, the exposure ranking proved to be the same. Cyclists were more exposed (median value of 8.1 µg/m³) than walkers (median: 7.9 µg/m³), followed by bus users (median: 7.4 µg/m³) and tramway (median: 7.1 µg/m³). Compared to cyclists, walkers were 2.4% less exposed, bus commuters 8.6% less and tramway users 12.2% less. Qiu and Cao (2020) also found that walkers were more exposed than bus commuters. Peng et al. (2021) and Wang et al. (2021) found the same exposure ranking (bike>walk>bus). They used a PMS3003 device, similar to PMS7003. According to Shen and Gao (2019), cyclists and pedestrians can be directly exposed to other local particle emissions along the road, which probably results in elevated PM concentrations in specific areas and times. In a study taking place in Nantes (France), Muresan and François (2018) stated that public transport users would accumulate 4–11 times less PM in their lungs than nearby pedestrians walking the same route. We decided to pursue all further analyses after having removed outliers in our dataset.

3.2 Comparison Between Travel Modes

Exposure levels are greatly influenced by the time of day (Figure 5). The morning session (S1) showed higher $PM_{2.5}$ concentrations, followed by the noontime (S2) and the afternoon session (S3).

Of all transport modes combined, S1 $PM_{2.5}$ median was 12.9% higher than S2, while S2 median was 15.3% higher than S3. In the tramway, diurnal variations seem to be reduced compared to other modes. deSouza, Lu, Kinney, and Zheng (2021) also found that time of day (evening/morning) had an influence. In their ANOVA analysis, travel mode explained 9% of the variability in $PM_{2.5}$ concentrations whereas time of day explained 8% variability.

All sessions considered, cyclists are the most exposed commuters. Abbass, Kumar, and El-Gendy (2021) studied morning and evening $PM_{2.5}$ peaks. In their work, daily exposure patterns when walking or cycling looked similar, whereas microbus concentrations behaved differently, and cycling resulted in exposure to the highest average $PM_{2.5}$ concentrations.

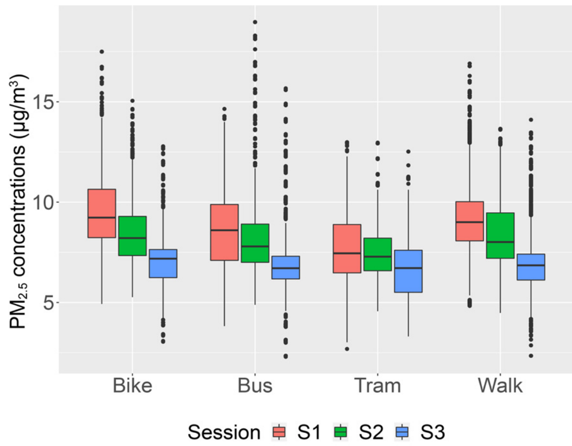

Figure 5: Boxplots of $PM_{2.5}$ concentrations by transport mode. Upper and lower whiskers show the ranges of 5% to 95%, the central dark lines indicate the median. The bars outside the box represent 1.5 times the interquartile range, and circles are outliers.

Per session, we observe the same $PM_{2.5}$ exposure ranking (bike > walk > bus > tramway) but, during S3, the levels measured in the bus get close to those measured in the tramway. When $PM_{2.5}$ levels are high (S1), the differences between the transport modes are important, but when the levels are low, during the afternoon (S3), the differences become less pronounced. This suggests that when PM levels are low, public transports no longer play a "protective" role against $PM_{2.5}$. In addition, relative differences between sessions are lower in the tramway than in the other transportation modes. This could mean that levels in the tramway are less influenced by background concentrations, which are higher in the morning.

3.3 Comparison with Reference Value

One of the objectives of this study was to compare the $PM_{2.5}$ values measured by the mobile sensors with those returned by the reference stations. The graph below (Figure 6) shows $PM_{2.5}$ levels measured by the mobile devices and the corresponding background reference levels. The hours marked in bold are the times when we carried out the most $PM_{2.5}$ measurements. As an example, the 10 am measurements were those that we were unable to perform as planned between 8 and 9 am. As this rarely happened, we got fewer observations for those extra hours.

In general, $PM_{2.5}$ levels given by the mobile sensors were lower than values given by background

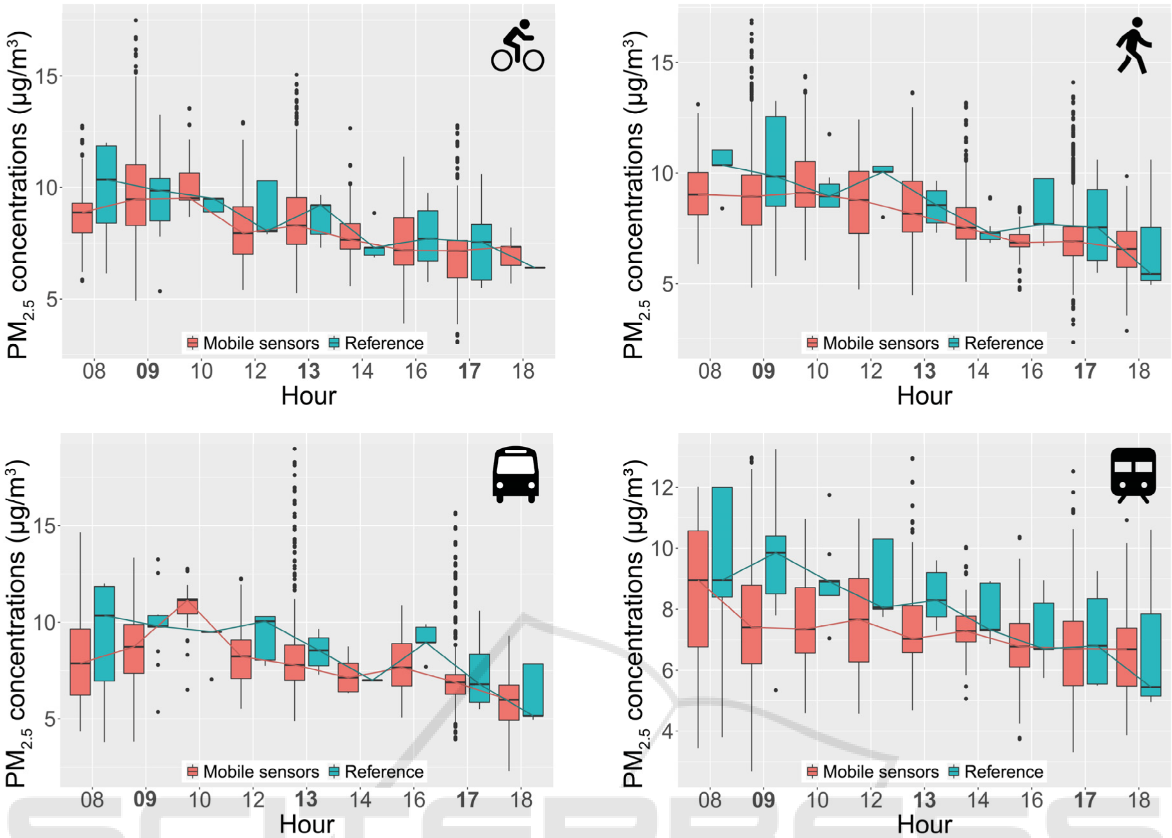

Figure 6: Comparison between values measured by mobile devices and reference values. The 9 o'clock boxplot corresponds to the values measured by mobile sensors between 8 and 9 am. The hours in bold are the ones where we had the more measurements taken by mobile devices.

stations, especially when considering hours when the counts were the highest (9, 13, and 17). This could come from microscale $PM_{2.5}$ variations, as $PM_{2.5}$ at the local scale could be affected by different factors. This was surprising that measured $PM_{2.5}$ values were lower than reference values, because we were in a traffic situation and the reference stations are located in a background environment. Both reference stations, situated in opened areas, could be exposed to more $PM_{2.5}$ which would be covered by the dense and high buildings of the city centre where experiments took place. The AirBeam2 calibration could also be an explanation. The ideal way to perform a calibration would have been to collocate our mobile devices directly with the reference station, without using a gold pod as an intermediary. It is also important to note that the calibration with the reference was performed at an hourly scale, and we had to apply it to values given at a fine scale (seconds). Knowing the RMSE related to step 1 calibration (Refer Figure 1), we could expect a maximal error of 0.7 µg/m^3. The average difference between reference and mobile values during S1 and S2 (considering 9, 13 and 17 o'clock timings) was about 1.1 µg/m^3. Therefore, the calibration error alone could most probably not explain the observed difference. Motlagh et al. (2021) used low-cost sensors to measure $PM_{2.5}$ in Helsinki and saw that roadside measurements were higher than reference values. But during spring or summer, the pollution levels in the train, bus or tramway were well below the ambient reference pollution levels. They attributed this to the fact that the transport fleet in Helsinki was quite modern and the indoor air heavily filtered. This should be the case for tramways in Grenoble. However, older buses might remain in operation, and the practice of using conditioned air depends on the weather and the driver. It would have been interesting to know if the air was filtered in the different buses and trams we used. Han et al (2021) also used low-cost sensors and observed that personal $PM_{2.5}$ levels were consistently lower than ambient concentrations. The Center for Advancing Research in Transportation Emissions, Energy, and Health (2019) measured exposure of urban cyclists in Atlanta (United States) with a PMS5003. They concluded that few segments recorded air quality worse than the background concentration. During most of the routes, riders experienced a better air quality than the one registered at the monitoring location.

In our study, wind could be an important factor determining $PM_{2.5}$ levels. We observed that wind speed values were increasing starting from 10 am (Figures 7 and 8). The relief around Grenoble could contribute to this phenomenon.

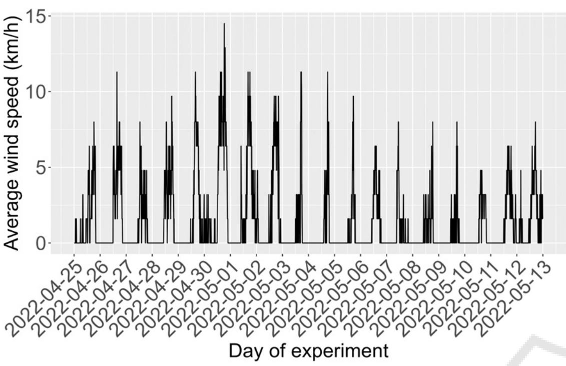

Figure 7: Wind speed values during the experiment.

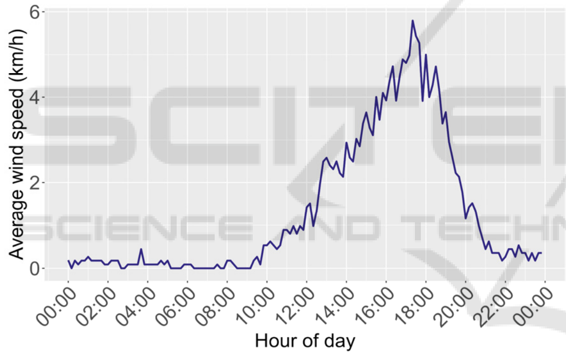

Figure 8: Average wind speed values between April 25, 2022 and May 12, 2022.

Interestingly, we observed that bus and tramway had levels close to the reference during S3 (Refer Figure 6). When PM levels in Grenoble were high, public transports provided an important advantage, but when PM levels were lower, close to their minimum, public transportation systems did not seem to offer this benefit any longer. Wang et al. (2021) also performed three daily measurement sessions (morning/noon/afternoon). Their GRIMM instrument showed that at lower pollutant levels, the concentrations registered in the bus were higher than the background levels. When pollutants levels were higher (noontime), the difference between inside and outside got larger, as in our study. They also observed lower levels of $PM_{2.5}$ compared to the reference when the pollutant levels were higher. Furthermore, by using a similar low-cost sensor (PMS3003), they found as well that when $PM_{2.5}$ levels were lower, the difference between reference levels and bus carriage levels was lower.

4 CONCLUSIONS

During this spring experiment, performed in 2022 at low pollutant levels, cyclists were more exposed than pedestrians, bus users and tramway commuters. This ranking was the same whether we removed outliers or not. We counted more outliers for walking than for cycling, tramway or bus.

When comparing exposure values to reference stations measurements: (1) pedestrian and cyclists' exposure generally stayed under background values, (2) public transportation systems were under reference values at 9 or 13 o'clock but when PM levels went lower, levels reached those of the reference value. Public transport users could be less exposed than commuters using active modes, except when ambient PM levels are low.

The time of day seems to influence exposure more than mode of transport, with a gradual concentration decrease throughout the day. Environmental parameters like wind might play a role in Grenoble. It would be interesting to reproduce this work during another season when wind speed is lower.

In the future, we will perform an inhalation dose calculation on the same dataset in order to consider breathing rate differences among commuting modes. In Grenoble, about 15% of the working population cycles to work (Agence de la Transition Écologique, 2015), which makes the problem of PM exposure more acute. However, we must emphasize that cycling helps prevent many chronic diseases and brings environmental benefits.

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ABBREVIATIONS

Acronym	Definition
ANOVA	Analysis of variance
Atmo AuRA	Atmo Auvergne-Rhône-Alpes
CAMS	Copernicus Atmosphere Monitoring Service
IoT	Internet of Things
mob1	AirBeam2 used by experimenter 1
mob2	AirBeam2 used by experimenter 2
PM	Particulate matter
PM_1	Particulate matter with aerodynamic diameter ≤ 1 µm
$PM_{2.5}$	Particulate matter with aerodynamic diameter ≤ 2.5 µm
PM_{10}	Particulate matter with aerodynamic diameter ≤ 10 µm
R^2	Coefficient of determination
RH	Relative humidity
RMSE	Root mean square error
ROMMA	Réseau d’Observation Météo du Massif Alpin

APPENDIX

Example of a measurement session

Date : 4/25/2022

Weather	humid, light rain, clouds
Wind	low
Traffic intensity	low

								Observations			
J1_S1 session	Experimenter	Code	Transport mode	Start "Chavant"	Arrival "Hôtel de Ville"	Start "Hôtel de Ville"	Arrival "Chavant"	Smokers	Idling vehicles	Crosses	Others
Wait 1	mob2	A_VM_CH	Wait at "Chavant"	7:50:18	7:54:08						
	mob2	A_T_CH	Wait at "Chavant"	7:54:09	7:59:12			7:57 smokers			
	mob1	A_VM_CH	Tram wait	7:50:07	7:54:46						
	mob1	A_B_CH	Bus wait	7:54:46	7:57:50						
Trip 1	mob2	T_CH_HV	Tram C	7:59:13	8:01:28						
	mob1	B_CH_HV	Bus C1	7:57:51	7:59:20				7:59 - 8:00 bus		
Waiting 2	mob2	A_B_HV	Bus wait			8:03:44	8:10:32				
	mob1	A_VM_HV	Walk wait			8:03:10	8:06:10				
Trip 2	mob2	B_HV_CH	Bus C1			8:10:33	8:12:00				
	mob1	M_HV_CH	Walk			8:06:11	8:14:25		8:09 garbage truck	8:13 stop	
Wait 3	mob2	A_T_CH	Tram wait	8:15:12	8:20:58						
	mob1	A_VM_CH	Bike wait	8:14:26	8:19:44						
Trip 3	mob2	T_CH_HV	Tram C	8:21:00	8:22:31						
	mob1	VD_CH_HV	Dedicated bike	8:19:45	8:21:51						
Wait 4	mob2	A_VM_HV	Walk wait			8:22:32	8:23:36				
	mob1	A_VM_HV	Walk wait			8:21:52	8:23:36				
Trip 4	mob2	M_HV_CH	Walk			8:23:37	8:30:40				
	mob1	M_HV_CH	Walk			8:23:36	8:30:40				
Wait 5	mob2	A_B_CH	Bus wait	8:31:52	8:34:00						
	mob1	A_VM_CH	Bike wait	8:30:41	8:33:12						
Trip 5	mob2	B_CH_HV	Bus C1	8:34:01	8:35:20						
	mob1	VD_CH_HV	Dedicated bike	8:33:13	8:35:37						
Wait 6	mob2	A_T_HV_RO	Tram wait			8:35:36	8:43:12				
	mob1	A_VM_HV	Walk wait			8:35:38	8:40:37				
Trip 6	mob2	T_HV_CH	Tram C			8:43:13	8:45:28				
	mob1	M_HV_CH	Walk			8:40:38	8:47:50				
Wait 7	mob2	A_VM_CH	Walk wait	8:45:29	8:48:30						
	mob1	A_VM_CH	Bike wait	8:47:51	8:51:45						
Trip 7	mob2	M_CH_HV	Walk	8:48:31	8:55:00			8:53 smoker			
	mob1	VD_CH_HV	Dedicated bike	8:51:46	8:54:10						
Wait 8	mob2	A_B_HV	Bus wait			8:55:20	8:57:49				
	mob1	A_T_HV_RO	Tram wait			8:56:22	8:59:17				
Trip 8	mob2	B_HV_CH	Bus C1			8:57:59	9:00:08				
	mob1	T_HV_CH	Tram C			8:59:18	9:01:02				