iSCAPE

Summary of air quality sensors and recommendations for application

D1.5
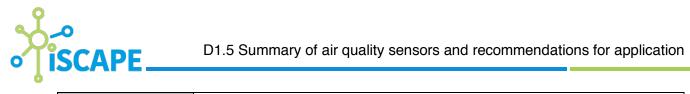
February 2016

Project Acronym and Name	iSCAPE - Improving the Smart Control of Air Pollution in Europe	
Grant Agreement Number	689954	
Document Type	Report	
Document version & WP No.	V0. 4	WP1
Document Title	Summary of air quality sensors and recommendations for application	
Main authors	Aakash C. Rai, Prashant Kumar, Francesco Pilla, Andreas Skouloudis, Guillem Camprodon	
Partner in charge	University of Surrey	
Contributing partners	UCD, JRC-IES, IAAC	
Release date	26 February 2016	

The publication reflects the author's views. The European Commission is not liable for any use that may be made of the information contained therein.

Document Control Page	
Short Description	*The aim of this report is to present state-of-the-art on air quality sensing and recommendations for their deployment in the field studies of the iSCAPE project as a deliverable for Task 1.5.This report presents an overview of the state-of-the-art in low-cost sensing of particulate and gaseous air pollutants through a comprehensive review of the scientific literature. Sensors and sensing technologies for monitoring particulate matter (PM), carbon monoxide (CO), ozone (O_3) and its precursors nitrogen dioxide (NO_2), and nitric oxide (NO) are reviewed with a focus on sensor selection based on the twin criteria of cost and performance.*

	General and project-specific guidelines for deploying and using the sensors are presented based on the literature review.		
Review status	**Action**	**Person**	**Date**
	Quality Check	*Coordination Team*	
	Internal Review	*Francesco Pilla, UCD* *Guillem Camprodon, IAAC*	15/02/2017
Distribution	Public		

Revision history			
Version	**Date**	**Modified by**	**Comments**
V0.1	02/11/2016	Aakash C. Rai and Prashant Kumar	The first draft, which included review of the low-cost PM sensors.
V0.2	20/12/2016	Aakash C. Rai and Prashant Kumar	Expanded the report by including low-cost sensors for O_3, NO_2, CO, and NO.
V0.3	22/02/2017	Aakash C. Rai and Prashant Kumar	Addressed reviewers' comments.
V0.4	26/02/2017	Aakash C. Rai and Prashant Kumar	WP1 leader's edits.
V0.5	23/10/2018	Abhijith Kooloth Valappil and Prashant Kumar	Addressed reviewers' comments

Statement of originality:

This deliverable contains original unpublished work except where clearly indicated otherwise. Acknowledgement of previously published material and of the work of others has been made through appropriate citation, quotation or both.
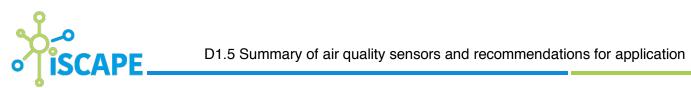
Table of Contents

Table of Contents

List of Tables

List of abbreviations and symbols

APS: aerodynamic particle sizer

BAM: beta attenuation monitor

CV: coefficient of variation

EC: electrochemical

FMPS: fast mobility particle sizer

FDMS: filter dynamics measurement system

LOD: limit of detection. $\mathrm{LOD} = 3 \times s_{\mathrm{blk}}$

MOS: metal-oxide-semiconductor

η_{d}: sensor detection efficiency. $\eta_{\mathrm{d}} = \dfrac{M_i}{RM_i}$

M_{Ai}: i^{th} value measured by sensor "A" being tested

M_{Ai}: i^{th} value measured by sensor "B" being tested

NA: not available

n: number of measurements

OPC: optical particle counter

R^2: coefficient of determination

R^2_{adj}: adjusted coefficient of determination

RH: relative humidity

RM_i: i^{th} reference measurement

RMSE: root mean square error. $\mathrm{RMSE} = \sqrt{\dfrac{1}{n}\sum_{i=1}^{n}(M_{Ai} - RM_i)^2}$

nRMSE: normalized root mean square error. $\mathrm{nRMSE} = \dfrac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_{Ai}-M_{Bi})^2}}{\frac{1}{2n}\sum_{i=1}^{n}M_{Ai}+M_{Bi}}$

s: standard deviation.

s_{blk}: the standard deviation of the sensor at zero concentration of the measured species.

SMPS: scanning mobility particle sizer

t_{lag}: time interval between a step change in input concentration and the first observable corresponding change in measurement response

t_{rise}: time interval between initial measurement response and 95% of final response after a step increase in input concentration

t_{90}: mean of $t_{0\text{-}90}$ (the time needed by the sensor to reach 90 % of the final stable value) and $t_{90\text{-}0}$ (the time needed to reach zero).

TEOM: tapered element oscillating microbalance

1 Executive Summary

This report presents a review of scientific literature about low-cost sensors available for monitoring harmful air pollutants such as particulate matter (PM), carbon monoxide (CO), ozone (O_3), and its precursors nitrogen dioxide (NO_2) and nitric oxide (NO). In the first section, we present a background about this emerging area of low-cost sensor (costing less than \$100 for the sensor or less than \$500 for the sensor plus the data acquisition system) based air pollution monitoring. Next, we discuss the state-of-the-art in low-cost sensing technology for monitoring different air pollutants focusing on their performance characterization. The subsequent section provides future research directions and recommendations for future technology development. The recommendations in terms of sensor selection for this project are discussed next. Finally, we discuss the major conclusions from this literature review.

2 Introduction

Outdoor air pollution is one of the major challenges of the 21st century, and is attributed to around 3.7 million deaths globally (WHO, 2014). It is estimated that 92% of the world's population lives in regions where air pollutant levels are higher than the WHO specified limits (WHO, 2016). In addition, air pollution is also responsible for causing environmental damage such as acid rain; haze; eutrophication; ozone depletion; damages to crop, forest, and wildlife; and global climate change (Fenger, 2009). Thus, there is a global drive to tackle this problem.

Traditionally, air pollution is monitored by measuring concentrations of various pollutants such as CO, NO, NO_2 Particulate Matter (PM), at fixed sites by using very accurate and expensive instrumentation. These monitoring sites are generally spread in and around cities, and provide temporal data (typically hourly) of the concentrations of different pollutants. For example, there are around 300 such sites distributed in the whole of UK (DEFRA, 2011). These are insufficient to provide accurate information about the spatio-temporal distribution of pollutants or identify pollution hotspots. Even though pollutant dispersion models are used to address this issue, their applicability is rather limited (Kumar et al, 2015).

Recent advancements in the field of sensors, digital electronics, and wireless communication technology have led to the emergence of a new paradigm for air pollution monitoring. This paradigm aims to gather high-resolution spatio-temporal air pollution data by using a ubiquitous network of low-cost sensor nodes for monitoring real-time (or near real-time) concentration of

different air pollutants. Such data can then be utilized for a variety of air pollution management tasks such as: (i) supplementing conventional air pollution monitoring; (ii) improving the link between pollutant exposure and human health; (iii) emergency response management, hazardous leak detection, and source compliance monitoring; and (iv) increasing community's awareness and engagement towards air quality issues.

Several review articles have already addressed this emerging area of sensor-based air quality management as summarized in Table 1. A majority of these articles focus on the needs, benefits, challenges, and future directions of a sensor based monitoring paradigm for different application areas (Bhanarkar et al, 2016; Castell et al, 2013; Kumar et al, 2016a; Kumar et al, 2015; Kumar et al, 2016b; Snyder et al, 2013; White et al, 2012). A few others discuss emerging sensor technologies for monitoring gaseous and/or particulate air pollutants (Aleixandre & Gerbolesb, 2012; White et al, 2012; Zhou et al, 2015). On-going air quality management campaigns using sensor-networks have been reviewed in a few other articles (Castell et al, 2013; Thompson, 2016). However, none of these reviews have addressed the aspect of *sensor selection* for developing a low-cost sensor node, costing a few 10's of dollars. The Air Sensor Guidebook of USEPA (Williams et al, 2014b) provides general guidelines regarding sensor selection but these guidelines are open ended and leave it for end users to carefully review a sensor's performance before purchasing it.

Therefore, we recognize a need for providing scientific guidance to end users in choosing the appropriate commercially available sensors based on the user's requirements and sensor characteristics. Through a comprehensive review of grey and scientific literature, we focus on the performance assessment of various low-cost sensors (costing less than \$100 for the sensor or \$500 for the sensor plus the data acquisition system) for measuring gaseous and particulate air pollutants. Both the particulate matter, and the gaseous pollutants of common interest in outdoor environments (i.e., CO, O_3, NO, and NO_2,) remain the focus of this report.

Author (year)		Study Focus
Aleixandre & Gerbolesb (2012)	&	Reviewed available commercial sensors for gaseous pollutants and compared their detection ranges with those specified in the European Directive on air quality 2008/50/EC.
White et al (2012)		Highlighted the synergistic opportunities available between sensor and wireless communication technologies for reducing human exposure to air pollutants.

Castell et al (2013)	Reviewed potential application areas of sensor technologies for air quality management. The article also provided a critical analysis of commercially available sensors for gas measurements, and emphasised the need for performance assessment of emerging sensor technologies under real-world conditions. Finally, the article summarized 24 different air quality management campaigns based on emerging sensor technologies.
Snyder et al (2013)	Discussed the changing paradigm of air pollution monitoring due to the emergence of portable air quality sensors. The paper also illustrates a few application areas for such sensors in managing air quality issues together with key challenges and possible solutions.
Koehler & Peters (2015)	Reviewed personal exposure assessment to particulate air pollution by using novel sensors developed over last 5–10 years. They also discussed new metrics (that go beyond traditional mass measurements) for evaluating the relationship between particulate matter and its health impacts.
Kumar et al (2015)	Reviewed the emergence of low-cost sensing technologies for managing air pollution in cities with respect to its need, state-of-the-art, opportunities, challenges, and future directions.
Zhou et al (2015)	Reviewed state of the art and future perspectives for different types of chemo-sensors for monitoring gases involved in environmental exhausts (CO_2, SO_2, NOx, VOCs), biological signalling (H_2S, NO, O_2), and toxic use (nerve gases, sulphur mustard).
Bhanarkar et al (2016)	Reviewed the issues and challenges in the design and deployment of wireless sensor nodes for outdoor air pollution monitoring.
Kumar et al (2016a)	Focused on solving the typical problem of deteriorating indoor air quality (IAQ) in building management programs aimed at conserving energy by proposing to use real-time sensing.
Kumar et al (2016b)	Highlighted the needs, benefits, challenges, and future outlook of monitoring indoor air quality (IAQ) using real-time sensors. The review also critically analysed the currently available sensor technologies available for monitoring different types of gaseous and particulate air pollutants.
Thompson (2016)	Reviewed current and emerging areas of analytical chemistry and sensor technology suitable for development of a low-cost sensing platform for monitoring air quality together with a summary of recent crowd-sourced sensing efforts.

Table 1: Summary of review articles focused on application of low-cost sensors for managing air pollution (articles published since 2010 have been included).

3 Current State of the Art

3.1 PM Sensors

The concentration of PM in air can be measured by several methods such as filter-based-gravimetric method, β-attenuation method, optical method, etc. However, the optical technique remains the method of choice for low-cost sensing due to its low cost and power requirements and quick response times. In this technique, a light source illuminates the particles, and then the scattered light from the particles is measured by a photometer. For particles with diameters greater than ~0.3 μm, the amount of light scattered is roughly proportional to their mass/number concentration. Particles smaller than ~0.3 μm do not scatter enough light, and cannot be detected by this method. The particles can be differentiated based on their size by either using an algorithm on the signal obtained from the scattered light or by attaching an impactor/filter at the inlet.

These low-cost optical sensors are available from a variety of manufacturers, and their general specifications are given in Table 2. The typical cost is around $10–100 for the sensor alone or between $100–500 for the sensing kits, which typically includes the sensor, microprocessor, data-logger, memory card, battery, and display. Sensors including the Sharp GP2Y1010AU0F, Samyoung DSM501A, Shinyei PPD42NS, and Shinyei PPD60PV cannot distinguish between particle sizes and typically report the concentration of particles with sizes greater than 0.5 μm as a single value for the PM concentration in air. The Dylos sensors rely on size discrimination by applying signal processing algorithms on the photometer's output. However, this method might result in significant misclassification of particles (Sousan et al, 2016b).The Sharp DN7C3CA006 sensor is the only sensor equipped with a virtual impactor that allows particles smaller than 2.5 μm to pass through the sensing zone. It is not known how the Plantower sensors perform size discrimination between particles. Thus, to monitor PM_{10} or $PM_{2.5}$ any of these sensors would be suitable, if an appropriate mechanism for size selection is applied (if not already provided by the manufacturer), except for the Sharp DN7C3CA006 that is clearly suited for monitoring only $PM_{2.5}$. The requirement for a size selection mechanism is less stringent for monitoring PM_{10} since particles larger than 10 μm are difficult to draw in the sensing zone, meaning that the raw output of the sensor would roughly correspond to PM_{10} concentration.

Many of these sensors have already been used in several air quality monitoring studies such as monitoring of ambient wood-smoke (Olivares & Edwards, 2015), risk husk in a rice mil (Zakaria et

al, 2014), cigarette smoke in garage (Rajasegarar et al, 2014), PM levels associated with source activities in homes (Olivares et al, 2012), and urban and rural backgrounds (Steinle et al, 2015). However, there is a huge gap in the scientific literature regarding issues related to the calibration and performance (especially long-term performance) of these sensors, which makes it difficult to assess the data quality and make comparisons between different investigations. Only a few studies have tested the performance of these low-cost PM sensors. A summary of those investigations is given in Table 3. Due to the lack of a standard calibration protocol, different studies have used different calibration methods, including chamber and field testing against a variety of reference instruments. These studies suggest the need for on-site calibration of individual sensors for the aerosol type to be measured since even the sensors of the same type can give different outputs under identical conditions.

Table 4 gives a summary of the performance characteristics of the tested sensors including their comparisons with reference measurements; precision (repeatability and reproducibility); limit of detection (LOD); sensitivity; and dependence on particle composition, size, humidity, and temperature. The sensors generally displayed moderate to excellent linearity ($R^2 > 0.5$) of response in all the investigations when compared with reference measurements. The sensors typically perform very well ($R^2 > 0.8$) when tested in laboratory conditions; however, their performance is generally lower in field deployments. This performance deterioration in real-world conditions is to be expected and can be attributed to the changing conditions of particle compositions, sizes, and environmental factors such as humidity and temperature.

Only a few investigations have reported the repeatability characteristics of the sensors as shown in Table 4. The sensor repeatability as measured by the CV generally lies between 5 to 30% for all the sensors and depends on the concentration range of measurements. Manikonda et al (2016) reported the reproducibility characteristics of three different PM sensors by comparing measurements conducted with two sensors of the same model under identical chamber conditions. Moderate to excellent reproducibility characteristics were reported when the sensor were exposed to cigarette smoke with nRMSE = 2.6–22.3% for the different sensors. However, the reproducibility characteristics significantly deteriorated when the sensors were exposed to Arizona Test Dust (ATD) with nRMSE = 46.1–118.2%. The reported variations between responses of sensors of identical models could be due to accumulation of particles in the sensing zone. This

effect would especially be pronounced when the sensors were exposure to ATD as compared to cigarette smoke since the former comprises of much larger particles than the latter.

The LOD for the sensors has been reported by several studies as given in Table 4. Wang et al (2015) reported that the LOD for the GP2Y1010AU0F, PPD42NS, and DSM501A sensors were 26.9 $\mu g/m^3$, 4.59 $\mu g/m^3$, and 4.28 $\mu g/m^3$, respectively, for PM concentrations less than 100 $\mu g/m^3$; and 26.1 $\mu g/m^3$, 6.44 $\mu g/m^3$, and 11.4 $\mu g/m^3$, respectively, for PM concentrations less than 1000 $\mu g/m^3$. Since the LOD for the GP2Y1010AU0F is reported to be very high it seems to be suitable only for monitoring places with high PM concentrations (> 100 $\mu g/m^3$), whereas the other three sensors seem suitable even at low PM concentrations (10–100 $\mu g/m^3$). However, it should be noted that the calibration curve for the GP2Y1010AU0F sensor had a large intercept that was not adjusted for while calculating its LOD in the study, which could be a possible reason for its seemingly high LOD. Thus, the suitability of the GP2Y1010AU0F sensor for monitoring low PM concentrations needs to be further investigated.

The dependence of sensor output on particle size and composition has been studied by a few investigations, and these factors were found to affect the output of the sensors by as much as 10 times as shown in Table 4 for the different sensors. The sensor output increases with the particle size since for the same mass concentration larger particles scatter more light, which results in higher reported concentrations (Wang et al, 2015). The difference in particle composition also impacts the scattering and absorption of light by them, which in turn influences the sensor output. For example, organic materials tend to absorb a higher proportion of incident light as compared to inorganic materials that typically absorb negligible radiation. This means that the optical sensors will report a much higher concentration of particles with organic compositions as compared to those with inorganic compositions even when measuring identical concentrations (Wang et al, 2015). Thus, it is necessary to calibrate the sensors for the expected range of particle sizes and compositions before usage.

Environmental factors such as humidity and temperature have also been found to influence the sensor outputs. Wang et al (2015) studied the impact of humidity on performance of the GP2Y1010AU0F, PPD42NS, and DSM501A sensors by using an SMPS as the reference instrument under chamber conditions. They found that the outputs of the sensors first increased, and then decreased as the humidity was increased from 20 to 90% RH. They attributed this effect on a combination of factors including the absorption of radiation by water causing an overestimate
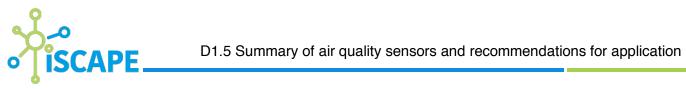
of particle concentrations, the unsuitability of SMPS as a reference instrument at high humidity conditions, and possibility of circuit failure in particle sensors at high humidity conditions. A few field investigations have also explored the influence of humidity on the response of Dylos and PPD42NS sensors (Gao et al, 2015; Han et al, 2016; Holstius et al, 2014; Jiao et al, 2016). Jiao et al (2016) did not find relative humidity to be associated with Dylos sensor's response; however, others found some association between sensor output and humidity. Nevertheless, this association was attributed to humidity being a confounding factor rather than having a causal relationship with the sensor output.

The impact of temperature on sensor output was found to be minimum by Wang et al (2015) in their chamber experiments, and the difference in response of GP2Y1010AU0F, PPD42NS, and DSM501A was between 10 to 20% for temperature variations from 5 to 32°C. A similar conclusion was also drawn by two different field investigations (Holstius et al, 2014; Jiao et al, 2016). Although Gao et al (2015) reported significant association between temperature and PPD42NS sensor's output, it was likely due to the temperature being a confounding variable. Olivares et al (2012) reported that the baseline response of the GP2Y1010AU0F sensor was linearly proportional to the temperature from 18 to 32°C; however, they did not report how much error was introduced in the measured mass concentrations due to temperature effects. Theoretically, light scattering and absorption are independent of temperature, which means that the temperature variations should not affect an optical sensor's output.

The suitability of such low-cost sensors for long term monitoring of PM is yet to be explored by the scientific community. We found only one field investigation by Jiao et al (2016), which reported that the value of R^2_{adj} improved from 0.45 to 0.56 when "days of use" was added as a predictor variable in their linear regression model between the sensor response and the reference measurements. Thus, it is possible that the response of PM sensors might change with time due to sensor aging and/or dust accumulation; however, it is also possible that "days of use" was just a confounding variable.
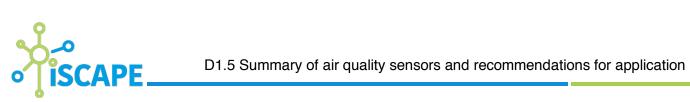
Model	Size (mm)	Weight (g)	Power supply	Maximum current consumption (mA)	Cost ($)	Detectable particle size	Concentration range of measurement
Sharp GP2Y1010AU0F	46×30×18	15	5 V DC	20	~10	Greater than 0.5 μm	0–600 μg/m^3

Sharp DN7C3CA006	50×44×20	52	5 V DC	180	~20	0.5–2.5 μm	25–500 μg/m³
Samyoung DSM501A	59×45×20	25	5 V DC	90	~15	Greater than 1.0 μm	0–1400 μg/m³
Shinyei PPD42NS	59×45×22	24	5 V DC	90	~15	Greater than 1.0 μm	0–28 particles/cm³
Shinyei PPD60PV	88×60×20	36	5 V DC	NA	~250	Greater than 0.5 μm	0–70 particles/cm³
Dylos DC 1100 Pro	178×114×76	544	110 V AC	NA	~300	0.5–2.5 μm and 0.5–10 μm in two size bins	0–106 particles/cm³
Dylos DC 1700	178×114×76	544	110 V AC or battery	NA	~400	0.5–2.5 μm and 0.5–10 μm in two size bins	0–106 particles/cm³
Plantower PMS 1003	65×42×23	NA	5 V DC	120	~ 20	0.3–1.0 μm, 1.0–2.5 μm, and 2.5–10 μm in three size bins	0–500 μg/m³
Plantower PMS 3003	65×42×23	NA	5 V DC	120	~ 20	0.3–1.0 μm, 1.0–2.5 μm, and 2.5–10 μm in three size bins	NA
Alphasense OPC-N2	75×64×60	105	5 V DC	175	~500	0.38–17 μm in 16 size bins	0.1–1500,000 μg/m³

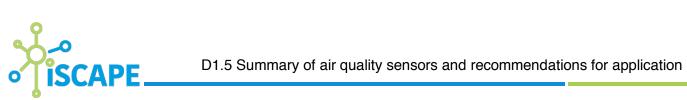*Table 2: Specifications of the different PM sensors given their respective manufacturers.*

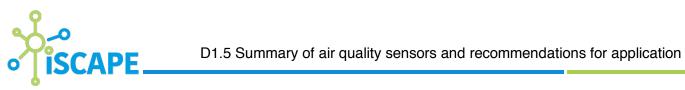| Article	Sensor(s) tested	Reference equipment used	Test conditions	Test site(s)	Summary
Olivares et al (2012)	Sharp's GP2Y1010AU0F	TSI AM510 'Sidepak'	PM concentration: ~ 0–3000 μg/m³ and temperature: 18–28 °C.	Test home in Auckland, New Zealand.	The sensor's baseline response was found to be linearly proportional to temperature, and each sensor required individual calibration curve. After proper calibration, the sensors performed very well with an R² value is 0.99.
Northcross et al (2013)	Dylos (modified by authors)	DustTrak 8520, EBAM	PM concentration: 0–1200 μg/m³.	Urban background in Richmond, CA and chamber experiments.	Compared the sensor's performance against reference in chamber by using polystyrene latex spheres, ammonium sulphate, and wood-smoke, and also tested it in urban ambient setting. The sensor's detection

					limit was found to be less than 1 $\mu g/m^3$, and the resolution was better than 1 $\mu g/m^3$.
Holstius et al (2014)	Shinyei PPD42NS	BAM 1020, GRIMM, DustTrak, Dylos DC1700	PM concentration: ~0–25 $\mu g/m^3$, humidity: ~10–60% RH, and temperature: ~15–40 °C.	Regulatory monitoring site in Oakland.	Found that the sensor had reasonably good accuracy when compared with 1h-averaged and 24h-averaged BAM data, with the R^2 being equal to 0.60 and 0.72, respectively. Temperature and humidity were found to have negligible association with the sensor measurements.
Alvarado et al (2015)	Sharp GP2Y10 and Samyoung DSM501A	DustTrak 8520	PM concentration: ~ 0–150 $\mu g/m^3$.	Chamber experiments.	The Samyoung sensor was found to have a low coefficient of correlation ($R^2 \sim 0.5$), while the Sharp sensor had a good correlation coefficient ($R^2 > 0.9$) with the reference. The calibrated Sharp sensor was then used for monitor dust particles after blasting at open-pit mine sites.
Austin et al (2015)	ShinyeiPPD42NS	TSI Aerosol Particle Sizer (APS) model 3321	PM concentration: ~0–800 $\mu g/m^3$.	Chamber experiments.	The sensors were found to have a linear response for PM concentrations below 50 $\mu g/m^3$, and thereafter a non-linear response, which saturated at 800 $\mu g/m^3$. It was also found that they can be reliably used for measuring particles from sizes 0.5–2.5μm; however, each sensor needs to be individually calibrated.
Gao et al (2015)	ShinyeiPPD42NS	DustTrak, E-BAM, and MiniVol	PM concentration: ~77–889 $\mu g/m^3$, humidity: 3–17% RH, and temperature: –3.5 to 19.2 °C.	Highly polluted urban area in Xi'an, China.	The sensors performed very well during the calibration phase with $R^2 > 0.85$; however, during the field deployment, the performance was moderate ($R^2 = 0.53$). These differences were attributed to differences in environmental conditions during the two periods.
Olivares & Edwards (2015)	SharpGP2Y1010AU0F	TEOM-FDMS	PM concentration: ~ 0–220 $\mu g/m^3$ and temperature: 6–26 °C.	An air quality monitoring site at Coles Place, New Zealand and	The sensor's baseline response was found to be stable and slightly dependent on temperature during chamber experiments; however, during field deployment the sensor's output exhibited a

				chamber experiments.	significant drift and dependence on temperature.
Steinle et al (2015)	Dylos DC1700	TEOM-FDMS	PM concentration: ~0–30 μg/m³.	An urban and rural sites around Edinburgh, Scotland	The sensor was found to performed well at both locations (R^2 = 0.9 at the rural background site, and R^2 = 0.7 at the urban background site with respect to reference), and its performance did not seem to have been impacted by aerosol composition. The investigation then used the sensor for personal exposure measurements.
Wang et al (2015)	Shinyei PPD42NS, Samyoung DSM501A, and Sharp GP2Y1010AU0F	SMPS, SidePak, AirAssure^{TM}	PM concentration: ~50–5000 μg/m³; humidity: 20–90% RH, and temperature: 5–32°C	Chamber experiments.	Tested the sensors for six performance criteria: (1) linearity of response, (2) precision of measurement, (3) Limit of Detection (LOD), (4) dependence on particle composition, (5) dependence on particle size, and (6) relative humidity and temperature influences. The sensors were found to be suitable for monitoring air pollution in heavily polluted areas; however, they must be individually calibrated before deployment.
Han et al (2016)	DylosDC1700	Grimm 11-R	PM concentration: ~0–400 μg/m³, humidity: 26–91% RH, and temperature: 6–29 °C.	Backyard of an urban home.	The study found good correlation (R^2 = 0.8) between the sensor measurements and the reference equipment for $PM_{2.5}$; however the correlation was moderate (R^2 = 0.5) for $PM_{10–2.5}$. Humidity and particle size were found to impact the association between the sensor and reference.
Jiao et al (2016)	Dylos DC1100-Pro, Dylos DC1100, Shinyei PPD60PV, Shinyei PPD42NS	MetOne BAM 1020 $PM_{2.5}$ monitor	Humidity: 11–100% RH and temperature: –12 to 33 °C.	Locations in and around a regulatory monitoring site in Decatur area in Atlanta, GA	The study reported variable performance characteristics for three different low-cost sensors with the R^2 values varying from 0.16–0.45 against reference measurements.
Manikonda et	Samyoung DMS501A, Dylos 1100 Pro,	TSI 3321 APS, Grimm	PM concentration:	Chamber experiments.	The study generally reported good R^2 values between the low-cost sensors and the reference

al (2016)	Dylos 1700, Sharp GP2Y1010AU0F	1.109 laser aerosol monitor, and TSI FMPS 3091.	~ 0–500 $\mu g/m^3$.		monitors; however, the sensors need to be carefully calibrated before usage.
Zikova et al (2016)	Samyoung DMS501A	Grimm 1.109	Indoor campaign: PM concentration: 4.6 $\mu g/m^3$ (median value), humidity: 60–70% RH, and temperature: 20–27 °C. Outdoor campaigns: PM concentration: 7.3–7.6 $\mu g/m^3$ (median values), humidity: 40–93% RH, and temperature: –7.8–15 °C.	One Indoor and two outdoor campaigns conducted inside and outside a residence in Potsdam, NY.	The study reported R^2 values between 0.07–0.46 when the low cost sensors were compared with the reference instrument. The sensor performance was found to improve when the averaging time of the measurements and the PM concentration were increased.
Sousan et al (2016b)	DylosDC1700, and Sharp models GP2Y1010AU0F and DN7C3CA006	APS, SMPS	PM concentration: ~30–6500 $\mu g/m^3$.	Chamber experiments.	Found that even the same type of sensors needed to be calibrated individually for a particular type of aerosol. However, once calibrated the sensors performed quite well when compared to the reference instrumentation (R^2 between 0.95–0.99), and also demonstrated good precision (CV < 8%).
Kelly et al (2017)	Plantower models PMS 1003 and PMS 3003, and Shinyei PPD42NS	Grimm 1.109, DustTrack II 8530, TEOM, BAM, and gravimetric methods.	Wind tunnel measurements: PM concentration: 200 – 850 $\mu g/m^3$ ($PM_{2.5}$). Field measurements: PM concentration:	Wind tunnel experiments and field measurements in an urban residential area of Salt	The study reported that the PMS1003/3003 sensors performed better than the reported performance of other low-cost PM sensors from other investigations, when compared with FRM measurements under similar conditions.

				0–70.6 μg/m³, humidity: 27–89% RH, and temperature: −8.9–15.9 °C.	Lake City, Utah, USA	
Jovaševi ć-Stojano vić et al (2015)	Dylos 1700	TSI 3330 Optical Particle Sizer and Grimm 1.108	PM concentration: ~1–1000 #/cm³, indoors and ~10–220 μg/m³, outdoors.		Indoor experiments inside a laboratory and field studies at an automatic monitoring station in Serbia.	The study reported R^2 values between 0.00–0.95 and 0.74–0.84, when the low-cost sensor was compared with the reference instrument indoors and outdoors, respectively.
Sousan et al (2016a)	Alphasense OPC-N2	APS, SMPS	PM concentration: 5–10,000 μg/m³ (PM_{10}).		Chamber experiments.	The study compared the performance of the low-cost Alphasense OPC-N2 with a research grade and significantly expensive OPC (Grimm 1.108), and found that the low-cost sensor can provide similar level of performance, if site-specific calibration is performed.
William s et al (2014a)	Dylos DC 1100	Grimm EDM 180 (FEM)	PM concentration: 0–46 μg/m³, humidity: 19–100% RH, and temperature: −3 to 26 °C.		Field experiments conducted in Durham, NC, USA	The study reported that the R^2 = 0.54 between outputs from the Dylos DC100 sensor and a reference equipment. It was also found that the output from the Dylos was slightly affected by humidity but not temperature.

Table 3: Summary of articles focused on performance assessment of low-cost PM sensors for air pollution monitoring

Model	Performance assessment
Sharp GP2Y1010AU0F	Comparison with reference measurements
	R^2 = 0.99 versus photometer in a test home (Olivares et al, 2012).
	R^2 = 0.92–0.98 versus photometer in chamber tests (Alvarado et al, 2015).
	R^2 = 0.72 versus TEOM-FDMS in an air monitoring site in Coles Place, New Zealand (Olivares & Edwards, 2015).
	R^2 = 0.42–0.93 and R^2 = 0.69–0.98 versus three different reference instruments in chamber tests with cigarette smoke and ATD, respectively, as part of the AirAssure platform (Manikonda et al, 2016).

R^2 = 0.84–0.99 versus three different reference instruments in chamber tests with cigarette smoke as part of the UBAS platform (Manikonda et al, 2016).

R^2 > 0.95 versus SMPS and APS in chamber tests (Sousan et al, 2016b).

R^2 = 0.98–0.99 versus photometer in chamber tests (Wang et al, 2015).

Repeatability

CV < 10%, for concentrations between 100 to 1000 μg/m^3, and CV ≈ 25% for concentrations below 100 μg/m^3 in chamber experiments (Wang et al, 2015)

CV < 6% during chamber experiments (Sousan et al, 2016b).

Reproducibility

nRMSE = 2.6–4.0% and 97–118% between identical sensors while measuring cigarette smoke and ATD, respectively, during chamber tests (Manikonda et al, 2016).

LOD

26.9 μg/m^3 for concentrations < 100 μg/m^3, and 26.1 for concentrations < 1000 μg/m^3 (Wang et al, 2015)

Dependence on particle composition

Particles with different composition (atomized aqueous solutions of NaCl, $C_{12}H_{22}O_{11}$, and NH_4NO_3) but roughly similar size distribution and mass concentration were found to give up to ten times difference in sensor output when compared to the SMPS (Wang et al, 2015).

Particles with different compositions (aerosolized salt solution, Arizona road dust, diesel fumes, and welding fumes) but same mass concentration were found to give up to three times difference in sensor output when compared to the SMPS + APS data corrected by gravimetric measurements (Sousan et al, 2016b).

Dependence on particle size

Sensor's output increased as the particle sizes increased for the same mass concentration measured by the SMPS. Particles with different sizes (300 nm, 600 nm, and 900 nm) were found to give up to 75% difference in sensor output (Wang et al, 2015).

Dependence on humidity

Sensor's output first increased as the humidity increased from 20% RH to 67% RH, and then decreased as the humidity increased further to 90% RH, for the same mass concentration measured by the SMPS. The maximum difference in output was about 40% (Wang et al, 2015).
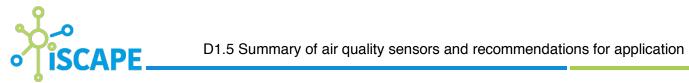
Dependence on temperature

Baseline response linearly proportional to temperature between 18 to 32 °C (Olivares et al, 2012).

Sensor's response probably not dependent on temperature (Olivares & Edwards, 2015).

Less than 15% difference in sensor output for temperatures between 5 to 32 °C for the same mass concentration (Wang et al, 2015).

Sharp DN7C3CA006	Comparison with reference measurements
	$R^2 > 0.98$ versus SMPS and APS during chamber tests (Sousan et al, 2016b).
	Repeatability
	CV < 8% during chamber experiments (Sousan et al, 2016b).
	Dependence on particle composition
	Particles with different compositions (aerosolized salt solution, Arizona road dust, diesel fumes, and welding fumes) but same mass concentration were found to give up to 1.2 times difference in sensor output when compared to the SMPS + APS data corrected by gravimetric measurements (Sousan et al, 2016b).
Shinyei PPD42NS	Comparison with reference measurements
	$R^2 = 0.90–0.94$ versus OPC, $R^2 = 0.64–0.70$ versus photometer, and $R^2 = 0.55-0.60$ versus BAM, measured in an urban area in California, USA (Holstius et al, 2014).
	$R^2 = 0.66–0.99$ versus an APS for concentrations below 50 μg/m^3, and a non-linear response thereafter during laboratory tests (Austin et al, 2015).
	$R^2 = 0.87–0.98$ versus photometer, $R^2 = 0.85–0.92$ versus BAM, and $R^2 = 0.53$ versus gravimetric measurements, measured at a highly polluted site in China (Gao et al, 2015).
	$R^2 = 0.93–0.96$ versus photometer in chamber tests (Wang et al, 2015).
	$R^2 < 0.16$ versus a BAM measured in a regulatory monitoring site in suburban Atlanta, Georgia, USA (Jiao et al, 2016).
	$R^2 = 0.50–0.80$ versus reference measurements in wind-tunnel experiments (Kelly et al, 2017).
	Repeatability
	CV < 10%, for concentrations between 400 to 1000 μg/m^3, and CV = 12–28% for concentrations below 400 μg/m^3 in chamber experiments (Wang et al, 2015).
	LOD
	1 μg/m^3 for concentration < 50 μg/m^3 (Austin et al, 2015).
	4.59 μg/m^3 for concentrations < 100 μg/m^3, and 6.44 for concentrations < 1000 μg/m^3 (Wang et al, 2015).
	Dependence on particle composition
	Particles with different composition (atomized aqueous solutions of NaCl, $C_{12}H_{22}O_{11}$, and NH_4NO_3) but roughly similar size distribution and mass concentration were found to give up to three times difference in sensor output when compared to the SMPS (Wang et al, 2015).
	Dependence on particle size
	Sensor's output increased as the particle size increased from 0.75 to 6 μm for the same mass concentration measured by the APS (Austin et al, 2015).
	Sensor's output increased as the particle sizes increased for the same mass concentration measured by the SMPS. Particles with different sizes (300nm,

600nm, and 900nm) were found to give up to six times difference in sensor output (Wang et al, 2015).

<u>Dependence on humidity</u>

Sensor's response moderately associated with humidity between 15 to 60% RH (Holstius et al, 2014).

Sensor response significantly associated with humidity between 3 to 17% RH (Gao et al, 2015).

Sensor's output first increased as the humidity increased from 20% RH to 67% RH, and then decreased as the humidity increased further to 90% RH, for the same mass concentration measured by the SMPS. The maximum difference in output was about 4 times (Wang et al, 2015).

<u>Dependence on temperature</u>

Minimal effect on sensor output ($R^2 = 0.01$) for temperatures between 15 to 40 °C (Holstius et al, 2014).

Sensor response significantly associated with the temperature (Gao et al, 2015).

10–20% difference in sensor output for temperatures between 5 to 32 °C for the same mass concentration (Wang et al, 2015).

Shinyei PPD60PV	<u>Comparison with reference measurements</u> $R^2 = 0.43$ versus a BAM measured in a regulatory monitoring site in suburban Atlanta, Georgia, USA. (Jiao et al, 2016)
Samyoung DSM501A	<u>Comparison with reference measurements</u> $R^2 \sim 0.5$ versus photometer during chamber tests (Alvarado et al, 2015). $R^2 = 0.88$–0.90 versus photometer in chamber tests (Wang et al, 2015). $R^2 = 0.92$–0.97 and $R^2 = 0.58$–0.97 versus three different reference instruments in chamber tests with cigarette smoke and ATD, respectively (Manikonda et al, 2016). $R^2 = 0.28$–0.29 and $R^2 = 0.07$–0.46 versus reference during tests inside and outside a residence, respectively (Zikova et al, 2016). <u>Repeatability</u> CV < 10%, for concentrations between 300 to 1000 μg/m³, and CV = 10–28% for concentrations below 300 μg/m³ in chamber experiments (Wang et al, 2015). <u>Reproducibility</u> nRMSE = 22.3% and 52.7% between identical sensors while measuring cigarette smoke and ATD, respectively, during chamber tests (Manikonda et al, 2016). Variable sensor-to-sensor reproducibility (Zikova et al, 2016). <u>LOD</u> 4.28 μg/m³ for concentrations < 100 μg/m³, and 11.4 for concentrations < 1000 μg/m³ (Wang et al, 2015). 8–10 μg/m³ (Zikova et al, 2016). <u>Dependence on particle composition</u>

Particles with different composition (atomized aqueous solutions of NaCl, $C_{12}H_{22}O_{11}$, and NH_4NO_3) but roughly similar size distribution and mass concentration were found to give up to 100% difference in sensor output when compared to the SMPS (Wang et al, 2015).

Dependence on particle size

Sensor's output increased as the particle size increased for the same mass concentration measured by the SMPS. Particles with different sizes (300nm, 600nm, and 900nm) were found to give up to 2.5 times difference in sensor output (Wang et al, 2015).

Dependence on humidity

Sensor's output first increased as the humidity increased from 20% RH to 67% RH, and then decreased as the humidity increased further to 90% RH, for the same mass concentration measured by the SMPS. The maximum difference in output was about 100% (Wang et al, 2015)

Dependence on temperature

10–20% difference in sensor output for temperatures between 5 to 32 °C for the same mass concentration (Wang et al, 2015).

Dylos DC models 1100 Pro and 1700 (both models use identical particle detection mechanism)	Comparison with reference measurements $R^2 = 0.97$–0.99 and $R^2 = 0.81$–0.99 versus photometer in chamber and field experiments, respectively (Northcross et al, 2013). $R^2 > 0.98$ versus OPC, $R^2 = 0.78$ versus photometer, and $R^2 = 0.58$ versus BAM during field measurements (Holstius et al, 2014). $R^2 = 0.9$ and 0.7 versus TEOM-FDMS at a rural and urban background sites, respectively (Steinle et al, 2015). $R^2 = 0.78$ and $R^2 = 0.48$ versus OPC for $PM_{2.5}$ and $PM_{>2.5}$, respectively, in an urban home's backyard (Han et al, 2016). $R^2 = 0.40$–0.45 versus a BAM measured in a regulatory monitoring site in suburban Atlanta, Georgia, USA (Jiao et al, 2016). $R^2 = 0.87$–0.95 and $R^2 = 0.64$–0.93 versus three different reference instruments in chamber tests with cigarette smoke and ATD, respectively (Manikonda et al, 2016). $R^2 > 0.91$ versus SMPS and APS during chamber experiments (Sousan et al, 2016b). $R^2 = 0.00$–0.44 and $R^2 = 0.77$–0.95 versus a TSI 3330 OPS in an indoor space with and without a strong PM source, respectively (Jovašević-Stojanović et al, 2015). $R^2 = 0.74$–0.84 versus Grimm 1.108 at automatic monitoring station in Serbia (Jovašević-Stojanović et al, 2015). $R^2 = 0.55$ versus an FEM PM analyser (Grimm EDM180) during field measurements (Williams et al, 2014a). Repeatability CV < 8% during chamber experiments (Sousan et al, 2016b). Reproducibility

nRMSE = 13.4% and 46.1% between identical sensors while measuring cigarette smoke and ATD, respectively, during chamber tests (Manikonda et al, 2016).

<u>LOD</u>

< 1 μg/m^3 (Northcross et al, 2013).

<u>Resolution</u>

< 0.1 μg/m^3 (Northcross et al, 2013).

<u>Dependence on particle composition</u>

Changes in aerosol composition (from continental air containing secondary inorganic aerosols to cleaner, sea salt dominated air originating over the Atlantic Ocean) did not seems to influence the performance of Dylos as compared to the reference (Steinle et al, 2015).

Particles with different compositions (aerosolized salt solution, Arizona road dust, diesel fumes, and welding fumes) but same mass concentration were found to give up to 3.5 times difference in sensor output when compared to the SMPS + APS data corrected by gravimetric measurements (Sousan et al, 2016b).

<u>Dependence on particle size</u>

η_d < 0.05 for particles less than 0.3μm in size, and η_d = 0.6–1.1 for sizes between 1.3–5 μm (Sousan et al, 2016b).

$\eta_d \approx 1$ versus OPC for PM$_{2.5}$ at mass median diameters (MMD) from 1.7 to 4.4 μm. $\eta_d \approx 0.25$, $\eta_d \approx 0.75$, and $\eta_d \approx 4$ versus OPC for PM$_{10-2.5}$ at MMD = 1.7 μm, 2.9 μm, and 4.4 μm, respectively (Han et al, 2016).

<u>Dependence on humidity</u>

η_d ranges from 0.8–1.1 and 0.5–1.6 for PM$_{2.5}$ and PM$_{>2.5}$, respectively, at humidity between 52–57% RH. $\eta_d > 1.3$ and $\eta_d > 2.0$ for PM$_{2.5}$ and PM$_{>2.5}$, respectively, at humidity between 61–71% RH (Han et al, 2016).

No improvement in R$^2_{adj}$ when humidity was added as a predictor variable (Jiao et al, 2016).

Slight correlation between sensor output and humidity (R^2 = 0.18) (Williams et al, 2014a).

<u>Dependence on temperature</u>

Very slight improvement in R$^2_{adj}$ (from 0.45 to 0.48) when temperature was added as a predictor variable (Jiao et al, 2016).

No correlation between sensor output and temperature (R^2 = 0.03) (Williams et al, 2014a).

<u>Days of use</u>

Significant improvement in R$^2_{adj}$ (from 0.45 to 0.56) when "days of use" was added as a predictor variable (Jiao et al, 2016).

Plantower PMS1003	<u>Comparison with reference measurements</u> R^2 = 0.69–0.99 and R^2 = 0.82–0.93 versus reference measurements in wind-tunnel and field experiments, respectively (Kelly et al, 2017). <u>LOD</u>

	0.7–3.2 μg/m^3 under laboratory conditions (Kelly et al, 2017).
	10.5 μg/m^3 during field testing (Kelly et al, 2017).
Plantower PMS3003	<u>Comparison with reference measurements</u> R^2 = 0.73–0.97 versus reference measurements in wind-tunnel experiments (Kelly et al, 2017).
Alphasense OPC-N2	<u>Comparison with reference measurements</u> R^2 = 0.94–0.99 versus SMPS and APS during chamber tests (Sousan et al, 2016a). <u>Repeatability</u> CV = 4.2–16% during chamber experiments (Sousan et al, 2016a). <u>Dependence on particle composition</u> Particles with different compositions (aerosolized salt solution, Arizona road dust, diesel fumes, and welding fumes) but same mass concentration were found to give up to 30 times difference in sensor output when compared to the SMPS + APS data corrected by gravimetric measurements (Sousan et al, 2016a). <u>Dependence on particle size</u> η_d = 0.83–1.01 for particles sizes between 0.5–5 μm (Sousan et al, 2016a).

Table 4: A summary of performance characteristics of low-cost PM sensors

3.2 Gas Sensors

To measure gaseous air pollutants, there are currently two types of low-cost sensors available in the market: (1) metal-oxide-semiconductor (MOS) sensors and (2) Electrochemical (EC) sensors.

The MOS sensors employ a metal oxide that changes its electrical properties (typically resistance) when exposed to the target gas. The change in the resistance can be easily measured and corresponds to the concentration of the gas. Such sensors are small in size (a few millimetres), lightweight (weighing a few grams), inexpensive (~$10), have quick response times, low detection limits and power requirements (~100 mW) (Aleixandre & Gerbolesb, 2012; Piedrahita et al, 2014). However, they have a non-linear response curve; and suffer from sensitivity to changes in humidity, temperature, pressure, and interfering gases (Spinellea et al, 2016).

The EC sensors used for air pollution monitoring are generally operated in amperometric mode, wherein the electrochemical reactions between the target gas and an electrolyte produce a current dependent on the gaseous concentration. The sensors typically consist of three electrodes, termed as working, counter, and reference. The target gas undergoes electrolysis (oxidation or reduction) at the working electrode, and generates electric charge which is balanced by the

reaction at the counter electrode. The electric current can be easily measured and corresponds to the concentration of the gas, and the response is either linear or logarithmic (Aleixandre & Gerbolesb, 2012). The reference electrode is typically employed in the sensor to ensure that the working electrode is maintained at the correct operating potential. These sensors typically have lower detection limits, power requirements (~100 μW), and sensitivity to changes in environmental conditions and interfering gases than MOS sensors, but are also slightly larger (few tens of millimetres in size), and more expensive (~$100) (Aleixandre & Gerbolesb, 2012; Piedrahita et al, 2014).

Low-cost gas sensors have been used in several air quality campaigns ranging from background pollutant measurements at rural and urban sites (Jiang et al, 2016; Spinelle et al, 2015b; Sun et al, 2016), measurements of roadside pollution (Mead et al, 2013; Popoola et al, 2016), mobile vehicular measurements (Hu et al, 2011; Suriano et al, 2015), source attribution (Heimann et al, 2015), and personal exposure monitoring (Jiang et al, 2011; Piedrahita et al, 2014). However, their performance characteristics are generally not well studied, and there exist only a few studies focused on assessment of sensors for monitoring gaseous pollutants as summarized in Table 5. Based on those studies, we have evaluated the performance of low-cost sensors for O_3, NO_2, NO, and CO in the following sub-sections.

Article	Sensor(s) tested	Reference instruments used	Test conditions	Test site(s)	Summary
Mead et al (2013)	1. Alphasense CO-AF (CO) 2. Alphasense NO-A1 (NO) 3. Alphasense NO2-A1 (NO$_2$)	Laboratory: Calibration gas standards. Field testing: Thermo Environmental Model 42C chemiluminescence analyser (NO/NO$_2$/NO$_x$)	Chamber experiments: CO: 0–160 ppb, NO: 0–130 ppb, and NO$_2$: 0–70 ppb	Laboratory calibration and roadside testing in and around Cambridge, UK	The sensors performed well during chamber experiments and roadside testing. The R^2 was greater than 0.99 during chamber testing for all the three sensors. The performance of the sensors was also found to be acceptable during roadside testing; however, the sensor outputs needs to be corrected by taking into account the effects of temperature, humidity, and interfering gases.
Piedrahi ta et al (2014)	1. SGX MICS-5525 (CO) 2. SGX MICS-2710 (NO$_2$) 3. SGX MICS-2611 (O$_3$)	1. Thermo Electron 48c monitor (CO), 2. Teledyne 200E (NO$_2$) 3. Teledyne 400E (O$_3$)	Chamber experiments: Temperature : 29–44°C, humidity: 20–60% RH, and CO: 0–4.2 ppm. Field testing: Temperature : ~ 0–35°C.	Chamber experiments and field testing at an air monitoring station in Denver, Colorado, and chamber experiments.	Proposed different calibration equations for converting the MOS sensor signal into concentration values. The calibration standard errors for CO, NO$_2$, and O$_3$ sensors were found to be 0.45 ppm, 8.4 ppb, and 6.1 ppb, respectively, during their field tests.
Williams et al (2014c)	1. AGT Environmenta l Sensor (O$_3$ and NO$_2$) 2. Dynamo sensor (O$_3$) 3. MICS 2611 (O$_3$) 4. MICS 2710 (NO$_2$) 5. Alphasense NO2-A1 (NO$_2$)	1. Thermo 42C chemiluminescen ce Nitrogen Oxides Analyser (NO$_2$/NO/NO$_x$) 2. 2B Model 205 UV Absorption Analyser (O$_3$) 3. Thermo Model 43C Pulsed Fluorescence Analyser (SO$_2$)	Temperature : ~ 5–45 °C and humidity: 20–100% RH	Glass chamber in laboratory	Evaluated the performance of various NO$_2$ and O$_3$ sensor for the following criteria: (1) linearity of response, (2) precision, (3) limit of detection (LOD), (4) resolution, (5) response time, and (6) interference equivalents.
Moltcha nov et al (2015)	1. Aeroqual SM50 (O$_3$)	Monitors at an AQM station.	Hot and humid conditions.	A residential neighbourho od and an AQM station in the coastal city	The ozone sensors performed well against the reference; however, there was a frequent need for calibration owing to the aging of sensors. To overcome this issue, the study proposed a

				of Haifa, Israel	calibration procedure that utilizes the data from nearby AQM stations.
Spinelle et al (2015a)	1. Alphasense O3B4 (O$_3$) 2. Citytech O3_3E1F (O$_3$) 3. Alphasense NO2B4 (NO$_2$) 4. Citytech NO2_3E50 (NO$_2$) 5. CairPolCairClip NO2 ANA (NO$_2$)	Thermo 42C Chemiluminescence Nitrogen Oxides Analyser (NO$_2$/NO/NO$_x$)	O$_3$: 0–110 ppb, NO$_2$: 0–150 ppb, humidity: 40–80% RH, and Temperature: 12–32°C.	Exposure chamber in laboratory with the ability to generate gaseous mixtures and independently control humidity, temperature, and wind velocity.	Tested different electrochemical sensors for measuring NO$_2$ and O$_3$ in an exposure chamber. They found that the calibration lines were linear for the tested sensors. They also explored the performance of the sensors for parameters including: (i) repeatability and LOD, (ii) drift, (iii) temperature and humidity effects, (iv) interference by gases, and (v) hysteresis effect.
Spinelle et al (2015b)	1. Alphasense O3B4 (O$_3$) 2. Citytech O3_3E1F (O$_3$) 3. Alphasense NO2B4 (NO$_2$) 4. Citytech NO2_3E50 (NO$_2$) 5. SGX-Sensotech MICS-2710 (NO$_2$) 6. SGX-Sensotech MICS-4514 (NO$_2$) 7. CairPolCairClip NO2 ANA (NO$_2$)	1. Thermo Environment 49C UV Photometric Analyser (O$_3$) 2. Thermo 42C Chemiluminescence Nitrogen Oxides Analyser (NO$_2$/NO/NO$_x$)	O$_3$: 1–83 ppb, NO$_2$: 1–63 ppb, humidity: 14–99% RH, and Temperature: –1 to 30 °C.	5 months duration at a semi-rural area in Italy	Compared the performances of several field calibration methods for low-cost sensors for NO$_2$ and O$_3$, including simple and multiple linear regressions and artificial neural network (ANN). It was found that the ANN method performed better compared to the linear regression techniques, and increased the association strength between estimated and reference data.
Borrego et al (2016)	1. SGX MICS-OZ-47 (O$_3$) 2. SGX MICS-2610 (O$_3$) 3. Alphasense O3B4 (O$_3$) 4. Alphasense NO2B4 (NO$_2$)	1. Airpointer - Recordum UV Fluorescence Analyser (SO$_2$) 2. Environnement AC31M Airpointer - Recordum Chemiluminesce	NO$_2$: ~ 0–52 ppb, CO: ~ 0.04–1.4 ppm, O$_3$: ~ 0–45 ppb, humidity: 40–90% RH, and	Field testing at an urban traffic location in Aveiro, Portugal for two weeks.	Tested several sensors as part of different sensor nodes for monitoring various air pollutants. They found significant differences between the performances of same sensor depending on the sensor node type.

	5. Citytech 3E50 (NO_2) 6. SGX MICS-2710 (NO_2) 7. Alphasense COB4 (CO) 8. Alphasense NOB4 (NO)	nce Analyser (NO_x) 3. Environnement CO11M Airpointer - Recordum Infrared Photometry Analyser (CO) 4. Environnement O341M Airpointer - Recordum Ultraviolet photometry Analyser (O_3)	temperature: 12–30 °C.		
Jiao et al (2016)	1. Aeroqual SM50 (O_3) 2. SGX MICS-2710 (NO_2) 3. SGX MICS-5525 (CO)	FRM/FEM	Humidity: 11–100% RH and temperature: –12 to 33°C.	Locations in and around a regulatory monitoring site in Decatur area in Atlanta, GA	The sensors displayed low to high R^2 values, ranging from 0.02–0.16, 0.05–0.57, and 0.68–0.94 for CO, NO_2, and O_3 sensors, respectively. The study also explored the impact of humidity, temperature, and days of usage on improving the predictions by the different sensors.
Popoola et al (2016)	1. AlphasenseCO-AF (CO) 2. AlphasenseNO-A1 (NO)	Chemiluminescence analyser (NO)	Temperature: 0–36 °C and NO: ~ 0–190 ppb.	Near a busy junction linking four major highways in Cambridge, UK.	The NO sensor's baseline response was found to be highly dependent on temperature, and its performance significantly improved after applying a temperature correction algorithm. The CO sensor's baseline response was found to be slightly affected by temperature.
Spinellea et al (2016)	1. UnitecSens 3000 (O_3) 2. SGX MICS OZ-47 (O_3) 3. SGX MICS 2610 (O_3) 4. FIS SP-61 (O_3)	Thermo Environment TEI 49C UV-photometer (O_3).	O_3: 0–110 ppb, humidity: 40–80% RH, and temperature: 12–32 °C.	Exposure chamber in laboratory with the ability to generate gaseous mixtures and independently control humidity, temperature,	Tested different MOS sensors for measuring ozone in an exposure chamber. They found that the calibration lines were non-linear for the tested sensors. They also explored the performance of the sensors for parameters including: (i) repeatability and LOD, (ii) drift, (iii) temperature and humidity effects, (iv) interference by gases, and (v) hysteresis effect.

					and wind velocity.
Sun et al (2016)	1. AlphasenseNO2B4 (NO_2) 2. Alphasense COB4 (CO)	Chamber experiments: 1. Teledyne T500U (NO_2) 2. Teledyne T300U (CO_2) Field testing: Data from Air Quality Monitoring Stations.	Chamber experiments: NO_2: 0–250 ppb, CO: 0-6 ppm, O_3: 0-300 ppb, humidity: 40-70% RH, and temperature: 15-21°C. Roadside testing: NO_2: ~ 10–210 ppb, CO: ~ 0.2–2.5 ppm, humidity: 33–89% RH, and temperature: 15–22 °C.	Chamber experiments, and field testing at a roadside Air Quality Monitoring Station in Central Hong Kong. These tests were followed by deployment along a marathon route in urban Hong Kong.	Found that the tested sensors performed very well under chamber and field conditions. The R^2 value was greater than 0.99 for the NO_2, CO, and O_3 sensors in chamber condition. The R^2 values were 0.90, 0.97, and 0.92 for the NO_2, CO, and $PM_{2.5}$ sensors, respectively, during roadside testing. The response for the CO sensor was unaffected by humidity and temperature, whereas response for the NO_2 sensor was affected by humidity, but not temperature.
Lewis et al (2016)	1. Alphasense OX-B421 (O_3) 2. Alphasense NO2-B4 (NO_2) 3. Alphasense CO-B4 (CO) 4. Alphasense NO-B4 (NO)	1. Gas standards (NO_2, CO, and NO) 2. UV photometric Thermo Scientific Model 49i analyser (O_3)	O_3: 0–350 ppb, NO_2: 0–160 ppb, CO: 0–200 ppb, NO: 1–160 ppb, SO_2: 0–40 ppb, humidity: 15–60% RH, and temperature: 20.2±0.7 °C.	Flow cell in laboratory.	Evaluated different gaseous sensors for cross-sensitivities to different gases and humidity. It was concluded that even though the cross-sensitivities might be low in absolute terms, high concentrations of interfering gases can produce a false positive/negative sensor response.
Castell et al (2016)	1. Alphasense OX-B421 (O_3) 2. Alphasense NO2-B42F (NO_2) 3. Alphasense CO-B4 (CO) 4. Alphasense NO-B4 (NO)	Chamber testing: 1. Gas standards 2. Teledyne API 300E non-dispersive infrared spectroscope (CO) 3. Teledyne API 200A Chemiluminescence Nitrogen	Chamber conditions: O_3: 0–170 ppb, NO_2: 0–105 ppb, CO: 0–5 ppm, NO: 0–385 ppb, humidity: 30% RH, and temperature: 20 °C.	Glass chamber in laboratory and different air quality monitoring stations in Norway.	Tested 24 identical sensor platforms (AQMesh), which comprised of commercially available low-cost sensors for monitoring O_3, NO_2, NO, and CO. It was found that the data quality obtained from the sensors was a serious concern due to poor reproducibility and stability characteristics of the sensors.

		Oxides Analyser (NO₂/NO/NOₓ) 4. Teledyne API 400 UV photometric analyser (O₃) Field testing: Data from the air quality monitoring stations.	Filed conditions: humidity: 19–98% RH, and temperature: –0.7 to 23.3 °C.		
Duvall et al (2016)	1. CairPol CairClip (NO₂)	Teledyne Model T200U chemiluminescence analyser (NO₂)	NO₂: 0–45 ppb, temperature: 20–35 °C and humidity: 25–93% RH	La Porte Airport, Houston, Texas, USA	The study compared the sensors performances with reference measurements, and also deployed them for community applications in schools and homes. It was noted that the community participation in collection of air pollution data can be used to complement data collected by experts.
Spinelle et al (2017)	1. Citytech NO_3E100 (NO) 2. SGX MICS-4514 (NO₂ and CO) 3. Figaro TGS-5042 (CO) 4. SGX MICS-4514 (CO)	1. Thermo 42C Chemiluminesce nce Nitrogen Oxides Analyser (NO₂/NO/NOₓ) 2. Horiba APMA 370 Non-dispersive Infrared Gas-Filter Correlation Spectroscopy (CO)	Field conditions: NO: 0–150 ppb, CO: 1–1.3 ppm, humidity: 14–99% RH, and Temperature: –1 to 30 °C. Chamber conditions: NO: 0–150 ppb, humidity: 40–80% RH, and temperature: 7–37 °C.	5 months duration at a semi-rural area in Italy and chamber experiments	Compared the performances of several field calibration methods for low-cost sensors for NO, CO, and CO₂, including simple and multiple linear regressions and artificial neural network (ANN). It was found that the ANN method performed better compared to the linear regression techniques, and increased the association strength between estimated and reference data.

Table 5: Summary of articles focused on performance assessment of low-cost gas sensors for air pollution monitoring

3.2.1 CO sensors

Five different models of CO sensors have been tested by the scientific community. Three of them are EC sensors and two are MOS sensors as given in Table 6. The EC CO sensors have been tested in both chamber and field conditions. In chamber conditions, the performances of the Alphasense CO-B4 and CO-AF was found to be excellent, with the R^2 values being greater than 0.99 (Castell et al, 2016; Mead et al, 2013; Sun et al, 2016). However, the field investigations report significant deterioration and variations in sensor performances as given in Table 6. Two field studies reported moderate to excellent R^2 values (0.53–0.97) for the CO-B4 sensor (Borrego et al, 2016; Sun et al, 2016). However, two other field studies have reported significantly lower R^2 values (0.17–0.45) for the CO-B4 and TGS-5042 sensors, when calibrating them with reference measurements (Castell et al, 2016; Spinelle et al, 2017). The differences in sensor performances could be attributed to the differences in testing conditions and methods. Note that sensor aging is also important for EC CO sensors since the sensor calibration curve can change significantly over time (Castell et al, 2016; Spinelle et al, 2017).

The LOD values for the CO-AF and CO-B4 sensors were 3 ppb (Mead et al, 2013) and 18–21 ppb (Castell et al, 2016; Sun et al, 2016), respectively. The repeatability and reproducibility characteristics of the EC CO sensor also seem reasonable (Table 6). Sun et al (2016) reported that the CO-B4 sensor was unaffected by humidity and temperature changes during chamber testing. Lewis et al (2016) reported that the CO-B4 sensor's response will increase by 0.53 ppb CO per percentage point increase in humidity, meaning that the maximum variation in output would be 53 ppb (when RH changes from 0 to 100%), which is quite low compared to typical ambient CO concentrations in the European Union (EU). The CO-AF sensor's baseline response was slightly affected by temperature (Popoola et al, 2016).

We computed that the cross-sensitivities to NO_2, O_3, NO, CO_2, and SO_2 would only change the response of the CO-B4 sensor only by −1.7 to 1.8 ppb from the data given by Lewis et al (2016). This was estimated by multiplying the gaseous cross-sensitivities with their corresponding ambient concentrations. For NO_2, O_3 and SO_2 concentrations, we used the EU specified limits. We used a representative value for background urban sites for CO_2 (400 ppb) and NO (15 ppb). The other investigations given in Table 6 also show that the response from EC CO sensors does not seem influenced by gaseous co-pollutants.

Only two MOS CO sensors were tested by the scientific community. The MICS-5525 CO sensor was tested by two investigations, and both reported extremely poor performance by this sensor.

The R^2 value was reported as 0.02–0.16 against reference measurements during field testing by Jiao et al (2016). Piedrahita et al (2014) calibrated eight identical MICS-5525 sensors under real-world conditions by using multiple linear regression and exponential models, which accounted for temperature and humidity effects. They reported median RMSE as 0.45 ppm and 3.56 ppm for the multiple linear regression and exponential models, respectively. They also reported that the sensor's response was dependent on the temperature and decreased linearly when the temperature was increased from 19°C to 40°C during chamber testing. The sensor-to-sensor reproducibility ranged from poor to moderate (Piedrahita et al, 2014).

The MICS-4514 sensor was tested by Spinelle et al (2017) under field conditions. They reported good R^2 values (0.76–0.78) with respect to reference measurements when the sensor was calibrated by using simple and multiple linear regression models. However, the same models performed poorly during the 4.5 months validation phase with R^2 values being less than 0.1. This indicates that the sensor aging is important factor for this sensor, and should be accounted when making long-term measurements.

Model	Performance assessment
Alphasense CO-B4 (EC sensor)	Comparison with reference measurements
	R^2 = 0.53-0.87 versus reference measurements when tested as parts of four different sensor nodes (Borrego et al, 2016)
	R^2 > 0.99 versus a Teledyne T300U CO_2 monitor during chamber testing (Sun et al, 2016).
	R^2 = 0.97 versus a regulatory grade monitor during testing near a roadside (Sun et al, 2016).
	R^2 = 0.99 during chamber testing (Castell et al, 2016).
	R^2 = 0.22–0.45 versus reference measurements during testing as part of 24 identical AQMesh platforms at an air quality monitoring station in Norway (Castell et al, 2016).
	LOD
	18 ppb (Sun et al, 2016).
	21 ppb (Castell et al, 2016).
	Repeatability
	s = 25 ppb at 1300 ppb CO (Castell et al, 2016).
	Cross sensitivity (in ppb/ppb for all gases)
	0.085 to NO_2, −0.053 to O_3, 0.00 to NO, 0.00 to CO_2, and −0.034 to SO_2, estimated from Lewis et al (2016).
	No cross-sensitivity to O_3, NO_2, and NO (Castell et al, 2016).

	Dependence on humidity/temperature
	Sensor's response not affected by humidity ranging from 40% to 70% RH (Sun et al, 2016).
	Sensor's response not affected by temperature ranging from 15–21°C (Sun et al, 2016).
	Response changed by 0.53 ppb of CO per percentage point increase in relative humidity, estimated from Lewis et al (2016).
	Long term performance
	Significant change in sensor behaviour during the six months of testing (Castell et al, 2016).
Alphasense CO-AF (EC sensor)	Comparison with reference measurements
	$R^2 > 0.99$ versus calibration gas standard during chamber testing (Mead et al, 2013).
	LOD
	3 ppb (Mead et al, 2013).
	Cross-sensitivity
	To NO: +0.24 ± 0.05% of measured CO at typical ambient NO concentration (Mead et al, 2013).
	To NO_2: +0.20 ± 0.08% of measured CO at typical ambient NO_2 concentration (Mead et al, 2013).
	Dependence on temperature
	Baseline response slightly affected by temperature ranging from 0–36°C (Popoola et al, 2016).
	Reproducibility
	High sensor-to-sensor reproducibility with $R^2 = 0.86$–0.95 (Mead et al, 2013).
Figaro TGS-5042 (EC sensor)	Comparison with reference measurements
	$R^2 = 0.17$–0.30 and 0.136–0.151 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2017).
	$R^2 = 0.27$–0.30 and 0.022–0.036 versus reference during calibration and validation phases, respectively, by using multiple linear regression with RH and T as additional predictors (Spinelle et al, 2017).
MiCS-5525 (MOS sensor)	Comparison with reference measurements
	Median RMSE was 0.45 ppm (range 0.38–0.52 ppm) during field testing of eight sensors by using a multiple linear regression equation that accounted for temperature and humidity effects (Piedrahita et al, 2014).
	Median RMSE was 3.56 ppm (range 2.85–5.33 ppm) during chamber testing of eight sensors for CO between 0 and 4.2 ppm by using an exponential based model equation that accounted for temperature and humidity effects (Piedrahita et al, 2014).

	R^2 = 0.02–0.16 versus a FRM/FEM measurements at a regulatory monitoring site in suburban Atlanta, Georgia, USA (Jiao et al, 2016).
	Dependence on temperature
	Sensor response decreased linearly with increasing temperature from 19°C to 40°C at a given CO concentration between 0 and 2.8 ppm during chamber testing (Piedrahita et al, 2014).
	Reproducibility
	Average sensor-to-sensor reproducibility with R^2 = 0.38–0.60 (Piedrahita et al, 2014).
MiCS-4514 (MOS sensor)	Comparison with reference measurements
	R^2 = 0.78 and 0.066–0.067 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2017).
	R^2 = 0.76–0.77 and 0.035–0.047 versus reference during calibration and validation phases, respectively, by using multiple linear regression with RH and T as additional predictors (Spinelle et al, 2017).

Table 6: Performance characteristics of low-cost CO sensors

3.2.2 O₃ Sensors

3.2.2.1 MOS Sensors

Table 7 gives a summary of the performance characteristics of the ozone sensors that have been tested by various scientific investigations. The studies conducted under real-world conditions have generally reported moderate to excellent correlations between these sensors and the reference instruments with R^2 values typically ranging from 0.77 to 0.94. Only one investigation (Borrego et al, 2016) has reported a very low R^2 value (R^2 = 0.12 for the MICS 2610 MOS sensor), which could be possibly due to sensor malfunctioning. Piedrahita et al (2014) conducted a measurement campaign at an AQMS in Denver, Colorado, and tested eight identical MOS sensors (model MICS 2611), and reported that the median RMSE was 6.1 ppb. Two studies have also tested different ozone sensors under chamber conditions. In the study by Williams et al (2014c), three different MOS based ozone sensors were tested in an exposure chamber under four different conditions (normal, hot, humid, and cold). The study generally found strong correlation between the responses of these sensors and the reference instrument with R^2 ranging from 0.88–0.99. However, it should be noted that the MICS-2611 sensor could not complete the tests under hot (temperature ≥ 50°C) and humid (RH ≥ 85%) conditions due to its response being unstable under those conditions. Four commercial MOS based ozone sensors were also tested by Spinellea et al (2016) in an exposure chamber. They reported the residual values for those sensors, as the difference between the reference concentration and the sensor measured value. At ozone

concentrations ranging from 0 to 110 ppb, the residual values were quite low (between 2.0–4.2 ppb) for three sensors; however, the residual value was as high as 13.3 ppb for the MICS-2610 sensors. Interestingly, the same sensor model was found to perform poorly in the investigation by Borrego et al (2016), as previously mentioned. Overall, the different MOS based ozone sensors (except for the MICS-2610 sensor) generally had good correlations and low residual values when compared against the reference methods.

The repeatability of the MOS ozone sensors has been studied by two investigations under chamber conditions (Spinellea et al, 2016; Williams et al, 2014c). The repeatability characteristics of the sensors were found to vary from excellent to poor as the standard deviations of their outputs ranged from as low as 0.2 ppb to as high as 46.2 ppb for the different sensors under different testing conditions. The sensor-to-sensor reproducibility has been quantified by two studies (Moltchanov et al, 2015; Piedrahita et al, 2014) through computing the R^2 values between the responses of several identical sensors under similar conditions. Moltchanov et al (2015) reported high reproducibility between sensors with $R^2 = 0.85$–0.98, whereas Piedrahita et al (2014) reported variable reproducibility values with R^2 ranging from 0.21–0.98 (median = 0.69).

The LOD of various MOS ozone sensors were calculated by the two chamber investigations (Spinellea et al, 2016; Williams et al, 2014c). Spinellea et al (2016) reported very low LOD values (0.5–1.5 ppb) for three different sensors; however, the LOD values were found to be much higher (5.1–23.4 ppb) for the three sensors tested by Williams et al (2014c). The reason for these differences is attributed to the different methods used for computing the LOD values. The study by Williams et al (2014c) has also reported the resolution of the three sensors under different conditions. The sensor with the best resolution had values between 0.1–3.6 ppb, whereas the sensor with the worst resolution had values between 2.6–37.7 ppb under different chamber conditions.

The response times of the different MOS based ozone sensors were reported by only two investigations (Spinellea et al, 2016; Williams et al, 2014c). Spinellea et al (2016) reported that the t_{90} for four different sensors varied from 4.4 to 89 minutes. The investigation by Williams et al (2014c) reported the t_{lag} and t_{rise} time of three different sensors. The t_{lag} and t_{rise} were between 1–3 mins and 5–8 mins, respectively. Thus, the t_{90} can be roughly calculated to be around 10 minutes (by summing the t_{lag} and t_{rise}). Once again, we find that the characteristics of different MOS based

ozone sensors can be quite different, with their response times, as characterized by t_{90}, ranging from just about 5 minutes to as high as 90 minutes.

Spinellea et al (2016) have reported the cross-sensitivities of four different MOS based ozone sensors to CO, CO_2, NO, NO_2, and NH_3 as given in Table 7. We computed the change in response for these four MOS sensors to be expected at typical urban settings by multiplying their sensitivity values with the corresponding gas concentrations expected in an urban environment (the procedure was described while discussing the cross-sensitivities of CO sensors). The estimated changes in sensor outputs were very low (–2.40 ppb to 1.95 ppb) for interferences by CO_2, NO, NO_2, and NH_3. However, CO interference (at 10 mg/m^3 CO concentration) would cause a significant change in the MOS sensor outputs (–6.81 ppb to 19.83 ppb), meaning that cross-sensitivity to CO could be important for such sensors. The cross sensitivity to SO_2 for three different MOS based ozone sensors were reported to be 0–7.5 ppb of ozone at > 200 ppb of SO_2 concentration by the Williams et al (2014c). Note that SO_2 concentration in urban settings is typically less than 20 ppb, so its effect on the O_3 sensors outputs is expected to be much smaller than that reported by Williams et al (2014c) for general air pollution monitoring applications. The study by Williams et al (2014c) also reported the cross-sensitivity to NO_2 for the Dynamo O_3 sensor to be 15.6 ppb at >200 ppb of NO_2 concentration, meaning that interference by NO_2 at high concentration could be a concern for this sensor. Based on the two investigations discussed above, it seems that cross-sensitivity to gaseous interferences by CO and NO_2 could impact the responses of MOS ozone sensors, which must be carefully accounted for before using them.

The response of the MOS based ozone sensors were also found to be significantly impacted by the environmental conditions such as temperature and relative humidity. During the chamber testing by Spinellea et al (2016), responses of the four different MOS sensors were found to decrease by 0.7–3.9 ppb of O_3 per °C increase in temperature from 12–32 °C. In these chamber tests, humidity was also found to impact the response of the sensors with the change being –3.1 to 0.84 ppb of ozone per percentage point increase in RH. However, the field testing conducted by Jiao et al (2016) did not find any association between the sensor's response and temperature or humidity. It is typically difficult to isolate the impact of secondary influencing factors (arising from changes in temperature or humidity) from the primary one (arising from changes in the ozone concentrations) in uncontrolled real-world conditions.

The drift in output for four different MOS-based sensors has been reported by Spinellea et al (2016). The sensors exhibited variable drift values, ranging from –0.009 to 0.081 ppb of O_3 per day during six months of chamber testing. This translates to –2 ppb to 15 ppb difference in sensor output for this duration depending on the model of the sensor. Moltchanov et al (2015) reported that the regression coefficients of the calibration curve of Aeroqual SM50 sensor changed with time possibly due to sensor aging and dust accumulation in the sensors due to episodic events such as rain or dust storms. However, Jiao et al (2016) did not find any association between the Aeroqual SM50 sensor's response and "days of use" during their field campaign suggesting that episodic dust accumulation might be the causing the sensor response changes reported by Moltchanov et al (2015). Clearly, this effect needs to characterized and compensated for, if long term O_3 measurements are to be made with these sensors.

3.2.2.2 EC Sensors

Three models of EC based ozone sensors have been tested by the scientific community as given in Table 7. Spinelle and co-workers studied the performances of both these sensors under chamber and field conditions. During chamber testing, the correlation between the sensor response and the reference instrument was found to be excellent with R^2 being greater than 0.99 for both the sensors (Spinelle et al, 2015a). A similar result was obtained by Castell et al (2016) for the OX-B421 sensor during chamber tests. However, while calibrating these sensors during field deployments, the O3B4 sensor showed a negligible R^2 value ($R^2 = 0.021$) with the reference, whereas the O3_3E1F sensors showed good R^2 values (0.84–0.88) with the reference (Spinelle et al, 2015b). Since the R^2 value between the O3B4 sensor and the reference was negligible, whereas the O3_3E1F sensor showed good R^2 values with the reference; it appears that the tested O3B4 sensor was faulty. Thus, we don't discuss additional results for this particular sensor obtained by Spinelle et al (2015b). In order to better calibrate the O3_3E1F, they used multiple linear regression models by including the concentration of NO_2 as an additional predictor, which increased the R^2 values to 0.85–0.94. The developed linear models (simple and multiple linear regression models) were then tested for another 4.5 months of field deployment in the validation phase of the study. During model validation, the model performance deteriorated significantly with the R^2 values being 0.67–0.81 and 0.58–0.82 for the simple and multiple linear regression models, respectively, for the O3_3E1F sensor. This clearly indicates that the response curves of the sensors were time variable possibly due to sensor aging and/or dust accumulation. Borrego et al (2016) reported $R^2 = 0.13$–0.70 during their field tests for the O3B4 sensor, when this sensor was

tested as a part of three different platforms under identical conditions. The different sensor platforms might use different signal processing techniques for converting the raw sensor response to the O_3 concentration, which might be reason for these disparities in the reported R^2 values. Castell et al (2016) tested twenty-four OX-B421 sensors as part of the AQMesh platform, and reported R^2 = 0.01–0.66 during a collocation campaign at a reference station. Their results clearly show that even for identical sensor and platform, drastically different results can be obtained, calling for careful quality control in the manufacturing process for both sensors and platforms.

As given in Table 7, majority of the data on performance characterization for three EC ozone sensors was obtained by Spinelle et al (2015a) and Castell et al (2016) under chamber conditions. They reported the standard deviations of the sensor outputs between 0.4 ppb to 1.91 ppb at 100 ppb ozone concentration, which indicates good repeatability characteristics of the sensors. The LOD was quite low (2.7–6.8 ppb), and the sensors also exhibited fast response times (t_{90} = 84–108 s).

A few investigations have tested the cross sensitivities of the EC ozone sensors to different gases as given in Table 7. From the table, it is clear that NO_2 interference is a big problem for the EC ozone sensors with the sensor response increasing by 0.76–1.00 ppb of O_3 per ppb of NO_2. Interferences by other gases do not seem to be a significant concern. We estimated that at typical urban concentrations of CO, CO_2, NO, NH_3, and SO_2 the sensor response would change by –3.8 to 0.05 ppb of O_3, (the estimation procedure is discussed in the section on CO sensors). However, NO_2 interference causes a significant increase in sensor outputs (16–21 ppb of O_3).

Humidity and temperature were found to affect outputs of EC O_3 sensors with the responses of different sensors changing by –0.022 to 1.3 ppb O_3 per percentage point increase in relative humidity and by 0.0 to 1.3 ppb O_3 per 1°C increase in temperature under laboratory testing (Lewis et al, 2016; Spinelle et al, 2015a). However, Spinelle et al (2015b) did not find any influence of humidity or temperature on the response of EC sensors during their field campaign. The differences between field and chamber measurements is attributed to the inability of field measurements in isolating the effect of a particular factor (such as temperature) on the sensor's response from other confounding factors (eg. gaseous interferences and sensor aging).

The drift of the sensor output was reported to be 0.016 and 0.142 ppb/day for the two sensors during the six months evaluation period. This translates to a total drift of 3 ppb and 26 ppb for the

O3B4 and O3_3E1F sensors, respectively, for the six months duration, meaning that the temporal variations in sensor response needs to be properly accounted for before conducting long term measurements. This is also supported from the observations of Castell et al (2016), who reported significant changes in an OX-B421 sensor's behaviour during six months of testing.

As evident from the above discussion, there is very limited amount of scientific literature available on the EC ozone sensors, which makes it extremely difficult to comprehensively assess their performance. Further studies are required to address this issue.

Model	Performance assessment
Aeroqual SM50 (MOS sensor)	<u>Comparison with reference measurements</u> R^2 = 0.77–0.94 versus an air quality monitoring station monitor in Haifa, Israel (Moltchanov et al, 2015). R^2 = 0.82–0.94 versus a FRM/FEM measurements at a regulatory monitoring site in suburban Atlanta, Georgia, USA (Jiao et al, 2016). <u>Reproducibility</u> High sensor-to-sensor reproducibility with R^2 = 0.85–0.98 (Moltchanov et al, 2015). <u>Dependence on humidity/temperature</u> No improvement in R^2_{adj} when humidity or temperature were added as a predictor variable (Jiao et al, 2016). <u>Drift/Stability</u> The slope and intercept values in the linear calibration curve changed significantly over time (Moltchanov et al, 2015). No improvement in R^2_{adj} when "days of use" was added as a predictor variable (Jiao et al, 2016).
UnitecSens 3000 (MOS sensor)	<u>Comparison with reference measurements</u> Maximum residual value equal to 2.0 ppb versus a UV-photometer during chamber tests (Spinellea et al, 2016). <u>Repeatability</u> s = 3.3 ppb at 100 ppb ozone (Spinellea et al, 2016). <u>LOD</u> 1.3 ppb (Spinellea et al, 2016). <u>Response time</u> t_{90} = 52±36 min(Spinellea et al, 2016). <u>Cross sensitivity (in ppb/ppm for CO_2 and ppb/ppb for other gases)</u>

0.015 to NO_2, -0.061 to NO, 2.3×10^{-3} to CO, -0.076 to CO_2, and -1.1×10^{-3} to NH_3 (Spinellea et al, 2016).

Dependence on humidity/temperature

Response changed by -0.65 ppb per percentage point increase in relative humidity from 40–80% RH (Spinellea et al, 2016).

Response changed by -3.86 ppb per °C increase in temperature from 12–32 °C (Spinellea et al, 2016).

Drift

0.070 ± 0.060 ppb/day during six months of chamber testing (Spinellea et al, 2016).

SGX MICS OZ-47 (MOS sensor)	Comparison with reference measurements
	$R^2 = 0.77$ versus reference (Borrego et al, 2016)
	Maximum residual value equal to 3.1 ppb versus a UV-photometer during chamber tests (Spinellea et al, 2016).
	Repeatability
	s = 2.0 ppb at 100 ppb ozone (Spinellea et al, 2016).
	LOD
	1.5 ppb (Spinellea et al, 2016).
	Response time
	$t_{90} = 9.8 \pm 7.8$ min (Spinellea et al, 2016).
	Cross sensitivity (in ppb/ppm for CO_2 and ppb/ppb for other gases)
	0.014 to NO_2, -1.9×10^{-3} to NO, -7.9×10^{-4} to CO, 2.2×10^{-3} to CO_2, and 8.0×10^{-4} to NH_3 (Spinellea et al, 2016).
	Dependence on humidity/temperature
	Response changed by -0.02 ppb per percentage point increase in relative humidity from 40–80% RH (Spinellea et al, 2016).
	Response changed by -0.7 ppb per °C increase in temperature from 12–32°C (Spinellea et al, 2016).
	Drift
	0.081 ± 0.010 ppb/day during six months of chamber testing (Spinellea et al, 2016).
SGX MICS-2610 (MOS sensor)	Comparison with reference measurements
	$R^2 = 0.12$ versus reference (Borrego et al, 2016)
	Maximum residual value equal to 13.3 ppb versus a UV-photometer during chamber tests (Spinellea et al, 2016).
	Repeatability
	s = 0.2 ppb at 100 ppb ozone (Spinellea et al, 2016).
	LOD
	0.5 ppb (Spinellea et al, 2016).
	Response time

t_{90} = 4.4±8.1 min (Spinellea et al, 2016).

Cross sensitivity (in ppb/ppm for CO_2 and ppb/ppb for other gases)

0.081 to NO_2, −0.016 to NO, −3.5×10⁻⁴ to CO, 1.9×10⁻³ to CO_2, and −1.0×10⁻³ to NH_3 (Spinellea et al, 2016).

Dependence on humidity/temperature

Response changed by 0.84 ppb per percentage point increase in relative humidity from 40-80% RH (Spinellea et al, 2016).

Response changed by −3.1 ppb per °C increase in temperature from 12-32°C (Spinellea et al, 2016).

Drift

−0.009±0.016 ppb/day during six months of chamber testing (Spinellea et al, 2016).

SGX MICS-2611 (MOS sensor)	Comparison with reference measurements

Median RMSE was 6.1 ppb (range 4.2–15.4 ppb) during field testing of eight sensors by using a multiple linear regression equation that accounted for temperature and humidity (Piedrahita et al, 2014).

R^2 = 0.88–0.95 versus reference during chamber testing in two different conditions (Williams et al, 2014c)

Repeatability

s = 6.5–46.2 ppb during chamber testing in two different conditions (Williams et al, 2014c).

Reproducibility

Variable sensor-to-sensor reproducibility with R^2 = 0.21–0.98 (Piedrahita et al, 2014).

LOD

LOD = 5.1–11.7 ppb during chamber testing under different conditions (Williams et al, 2014c).

Resolution

Resolution = 0.1–3.6 ppb during chamber testing in four different conditions (Williams et al, 2014c).

Response time

t_{lag} = 1–3 min during chamber testing in two different conditions (Williams et al, 2014c).

t_{rise} = 5–8 min during chamber testing in two different conditions (Williams et al, 2014c).

Cross-sensitivity

The sensor showed a response equivalent to 0 ppb O_3 at > 200 ppb of SO_2 (Williams et al, 2014c).

FIS SP-61 (MOS sensor)	Comparison with reference measurements

Maximum residual value equal to 4.2 ppb versus a UV-photometer during chamber tests (Spinellea et al, 2016).

Repeatability

s = 19.8 ppb at 100 ppb ozone (Spinellea et al, 2016).

Response time

t_{90} = 89±111 min(Spinellea et al, 2016).

Cross sensitivity (in ppb/ppm for CO_2 and ppb/ppb for other gases)

0.024 to NO_2, 0.13 to NO, 9.9×10^{-4} to CO, −1.2×10^{-2} to CO2, and 3.0×10^{-2} to NH_3 (Spinellea et al, 2016).

Dependence on humidity/temperature

Response changed by −0.46 ppb of O_3 per percentage point increase in relative humidity from 40-80% RH (Spinellea et al, 2016).

Response changed by −2.3 ppb of O_3 per °C increase in temperature from 12-32°C (Spinellea et al, 2016).

Drift

−0.007±0.180 ppb/day during six months of chamber testing (Spinellea et al, 2016).

AGT Environmental Sensor (MOS sensor)	Comparison with reference measurements

R^2 > 0.98 versus reference during chamber testing in four different conditions (Williams et al, 2014c).

Repeatability

s = 2.6–13.6 ppb during chamber testing in four different conditions (Williams et al, 2014c).

LOD

LOD = 14.7–23.4 ppb during chamber testing in four different conditions (Williams et al, 2014c).

Resolution

Resolution = 2.6–37.7 ppb during chamber testing in eight different conditions (Williams et al, 2014c).

Response time

t_{lag} = 1 min during chamber testing in four different conditions (Williams et al, 2014c).

t_{rise} = 3–6 min during chamber testing in four different conditions (Williams et al, 2014c).

Interference

The sensor showed a response equivalent to 7.5 ppb O_3 at > 200 ppb of SO_2 (Williams et al, 2014c).

Dynamo Sensor (MOS sensor)	Comparison with reference measurements

$R^2 > 0.97$ versus reference during chamber testing in four different conditions (Williams et al, 2014c).

Repeatability

s = 3.3–7.0 ppb during chamber testing in four different conditions (Williams et al, 2014c).

LOD

LOD = 14.9–17.6 ppb during chamber testing in four different conditions (Williams et al, 2014c).

Resolution

Resolution = 2.0–11.7 ppb during chamber testing in eight different conditions (Williams et al, 2014c).

Response time

t_{lag} = 1 min during chamber testing in four different conditions (Williams et al, 2014c).

t_{rise} = 2–5 min during chamber testing in four different conditions (Williams et al, 2014c).

Interference

The sensor showed a response equivalent to 2.9 ppb and 15.6 ppb of O_3 at > 200 ppb of SO_2 and > 200 ppb of NO_2, respectively (Williams et al, 2014c).

Alphasense O3B4 (EC sensor)	Comparison with reference measurements

R^2 = 0.021 versus reference measurements during calibration by using simple linear regression (Spinelle et al, 2015b)

$R^2 > 0.99$ during chamber testing (Spinelle et al, 2015a).

R^2 = 0.13–0.70 versus reference when tested as parts of three different sensor platforms (Borrego et al, 2016).

Repeatability

s = 0.4 ppb at 100 ppb O_3 (Spinelle et al, 2015a).

LOD

6.8 ppb (Spinelle et al, 2015a).

Response time

t_{90} = 84 s (Spinelle et al, 2015a).

Cross sensitivity (in ppb/ppm for CO and CO_2 and ppb/ppb for other gases)

0.92 to NO_2, −0.042 to NO, −0.066 to CO, 2×10^{-4} to CO_2, and 2.5×10^{-4} to NH_3 (Spinelle et al, 2015a).

Dependence on humidity/temperature

Response changed by 0.40 ppb of O_3 per percentage point increase in relative humidity from 40-80% RH (Spinelle et al, 2015a).

Not affected by increase in temperature from 12–32°C (Spinelle et al, 2015a).

Drift

< 0.016 ppb/day during six months of chamber testing (Spinelle et al, 2015a).

Citytech O3_3E1F (EC sensor)	Comparison with reference measurements
	$R^2 > 0.99$ versus reference measurements during chamber testing (Spinelle et al, 2015a).
	$R^2 = 0.84–0.88$ and 0.67–0.81 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2015b)
	$R^2 = 0.85–0.94$ and 0.58–0.82 versus reference during calibration and validation phases, respectively, by using multiple linear regression with NO_2 concentration as an additional predictor (Spinelle et al, 2015b).
	Repeatability
	s = 0.6 ppb at 100 ppb O_3 (Spinelle et al, 2015a).
	LOD
	2.7 ppb (Spinelle et al, 2015a).
	Response time
	$t_{90} = 108$ s (Spinelle et al, 2015a).
	Cross sensitivity (in ppb/ppm for CO and CO_2 and ppb/ppb for other gases)
	0.76 to NO_2, –0.011 to NO, 7.0×10^{-5} to CO, 3.5×10^{-3} to CO_2, and 1.6×10^{-3} to NH_3 (Spinelle et al, 2015a).
	Dependence on humidity/temperature
	Response changed by –0.022 ppb of O_3 per percentage point increase in relative humidity from 40–80% RH (Spinelle et al, 2015a).
	Response changed by 1.3 ppb of O_3 per °C increase in temperature from 12–32°C (Spinelle et al, 2015a).
	Not affected by humidity (Spinelle et al, 2015b)
	Not affected by temperature (Spinelle et al, 2015b)
	Drift
	< 0.142 ppb/day during six months of chamber testing (Spinelle et al, 2015a).
Alphasense OX-B421 (EC sensor)	Comparison with reference measurements
	$R^2 = 0.99$ versus reference measurements during chamber testing (Castell et al, 2016).
	$R^2 = 0.01–0.66$ versus reference measurements during testing as part of 24 identical AQMesh platforms at an air quality monitoring station in Norway (Castell et al, 2016).
	Repeatability
	s = 1.91 ppb at 100 ppb O_3 (Castell et al, 2016).
	LOD
	1.8 (Castell et al, 2016).
	Cross sensitivity (in ppb/ppm for CO and CO_2 and ppb/ppb for other gases)

1.00 to NO_2, –0.251 to NO, 0.00 to CO, 2.2×10^{-1} to CO_2, and –0.034 to SO_2, estimated from Lewis et al (2016).

No cross-sensitivity to NO and CO (Castell et al, 2016).

Dependence on humidity/temperature

Response changed by 1.3 ppb of O_3 per percentage point increase in relative humidity, estimated from Lewis et al (2016).

Stability

Significant change in sensor behaviour during the six months of testing (Castell et al, 2016).

Table 7: Performance characteristics of low-cost O_3 sensors

3.2.3 NO₂ Sensors

3.2.3.1 MOS sensors

Three different models of MOS NO_2 sensors have been tested by various scientific investigations as given in Table 8. During chamber testing of two different MOS NO_2 sensors (AGT Environmental and MICS-2710) under four different conditions, Williams et al (2014c) reported excellent correlations ($R^2 > 0.98$) between the sensor responses and the reference instrumentation. However, it should be noted that only the AGT Environmental sensor could complete the tests under all four conditions, whereas the MICS-2710 sensor could not complete the tests under "normal" and "cold" conditions due to problems with its stability. MOS NO_2 sensors have also been deployed in a few field investigations. Spinelle et al (2015b) have reported poor R^2 values ($R^2 \approx 0.2$) between the responses of two different MOS NO_2 sensors (MICS-2710 and MICS-4514) and the reference measurements during the two weeks calibration period. To better model the sensor responses, they also used multiple linear regression with the concentrations of O_3 and NO and temperature as additional predictors, which improved the R^2 values to 0.52–0.79 during the calibration phase for both sensors. The researchers further tested the models by using them for future measurements during the 4.5 months validation period. They found that the performances of both the simple and multiple linear regression models were very poor during the validation period with reported values of R^2 being ~0.1, which points to the aging of the sensors. Thus, sensor aging needs to be properly understood and compensated for, before long-duration measurements can be made; otherwise, frequent sensor calibration would be required. Borrego et al (2016) and Jiao et al (2016) tested the MICS-2710 sensor under field conditions, and reported R^2 less than 0.1 between the sensor response and the reference measurements. Another field investigation by Piedrahita et al (2014) tested six MICS-2710 sensors, and found the

measurement errors to be acceptable. They reported the median RMSE value equal to 8.4 ppb by using a multiple linear regression model that accounted for temperature and humidity effects on the sensor's response.

From the discussion above, it seems that a simple linear relationship between the responses of the MOS NO_2 sensors and the reference measurements is achieved only under laboratory conditions, but not under field conditions. This is because, there reportedly are various factors such as gaseous interference, humidity, and temperate, which influence the sensor's output, and need to be included while modelling the response of the sensor. Furthermore, sensor aging also seems to be an important characteristic of such sensors that changes the response of the sensor with time. Therefore, in order to conduct field measurements of NO_2 with MOS sensors, the sensors need to be properly and frequently calibrated by accounting for the different factors that can influence their response.

The repeatability characteristics of two different MOS NO_2 sensors under chamber conditions has been found to be reasonable by one investigation (Williams et al, 2014c) with the standard deviations of their repeated measurements lying between 1.2–7.5 ppb under different conditions. The sensor-to-sensor reproducibility for the MICS-2710 sensors was found to be high under field conditions (Piedrahita et al, 2014) as given in Table 8. Based on these limited studies, it seems that the repeatability and reproducibility characteristics of MOS NO_2 sensors are reasonably good.

The performance metrics of LOD, resolution, response time, and cross-sensitivity have only been reported by only one chamber investigation for two MOS NO_2 sensors under different conditions (Williams et al, 2014b). The LOD values varied between 6.3–26.6 ppb, and the resolution was between 0.1–6.8 ppb for the two sensors under different test conditions. The t_{lag} value for both the sensors was 1 minute. However, the t_{rise} differed significantly between the two sensors, varying from 21–33 minutes for the MICS-2710 sensor and from 5–20 minutes for the AGT Environmental sensor. Thus, we can crudely approximate t_{90} (as the sum of t_{lag} and t_{rise}) to vary between 6–34 minutes. The cross-sensitivity to SO_2 was reported to be 0 ppb and 19.5 ppb of NO_2 at >200 ppb SO_2 concentration for the MICS-2710 and the AGT Environmental sensor, respectively. Thus, it seems that depending on the specific test conditions and the model of the sensor; the LOD, resolution, response times, and cross-sensitivities can be significantly different.

3.2.3.2 EC sensors

Table 8 summarizes the performance characteristics of the EC NO_2 sensors tested by scientific investigations. The sensor responses show excellent correlation with the reference measurements with $R^2 > 0.9$ being reported by a few investigations under chamber conditions for four different sensors (Table 8). Expectedly, the correlation between the sensor response and the reference gets deteriorated under real world conditions. Borrego et al (2016) reported R^2 values between 0.06–0.89 for the NO2-B4 sensor, when tested as part of four different sensor platforms during field testing. This was possibly due to different signal processing algorithms used by the different platforms. They also reported $R^2 = 0.89$ for another EC NO_2 sensor. Mead et al (2013) and Sun et al (2016) conducted roadside measurements of NO_2 with an EC sensor, and reported R^2 values of ~0.9 after applying correction algorithms for interference by O_3 and humidity, respectively. Castell et al (2016) tested twenty-four EC NO_2 sensors (used in the AQMesh platform), and reported variable R^2 values (0.04–0.52) during their field campaign, which once again emphasises the requirement for quality control in the manufacturing of the sensor and platform. Another field campaign by Spinelle et al (2015b) tested the performance of three different NO_2 EC sensors. They reported R^2 values between 0.001–0.46 for the different sensors tested during the two weeks calibration period. To obtain better agreement between the sensor responses and the reference measurements, they employed a multiple linear regression model by using O_3 concentration, temperature, and humidity as additional predictors. This led to R^2 values ranging from 0.35–0.77, which was a significant improvement over the R^2 values previously obtained by the simple linear regression model. They also found that the agreement between the measurements from EC sensors and the reference was very poor ($R^2 < 0.1$ for all the sensors) during the validation phase of their campaign due to sensor aging. Clearly, the field campaigns point out that the EC NO_2 sensor responses are affected by O_3 concentration, temperature, relative humidity, aging, and manufacturing variations, which should be accounted for, while calibrating and using these sensors.

The repeatability characteristics of EC NO_2 sensors have been reported by only a few chamber investigations. The standard deviations for repeated measurements were between 0.8–2.9 ppb at 100 ppb NO_2 concentration for three different sensors (Castell et al, 2016; Spinelle et al, 2015a), whereas Williams et al (2014c) reported the standard deviation to be 4.6 and 23.3 ppb for a sensor tested under two different conditions. The values reported by Williams et al (2014c) are much higher than those reported by the other two investigations probably due to differences in sensor

models and testing methodologies. The sensor-to-sensor reproducibility was reported to be excellent ($R^2 > 0.94$) by Mead et al (2013). Thus, the EC NO_2 sensors' repeatability and reproducibility characteristics seem acceptable; however, more research is required to confirm this.

A few investigations have reported the LOD value for the EC NO_2 sensors. Spinelle et al (2015a) reported the LOD values for three different sensors, Mead et al (2013), Castell et al (2016), and Sun et al (2016) reported LOD values for one sensor each, and Williams et al (2014b) reported the LOD values for one sensor under two different chamber conditions. The reported values are 0.5–8.6 ppb, 1 ppb, 2.8 ppb, 6 ppb , and 11.6–29.4 ppb according to Spinelle et al (2015a), Mead et al (2013), Castell et al (2016), Sun et al (2016), and Williams et al (2014b), respectively. The values reported by Williams et al (2014c) are much higher than those reported by other investigations since they used a different methodology to compute the LOD values as compared to that used by the other studies. Only one investigation (Williams et al, 2014c) has reported the resolution value for one EC NO_2 sensor, which lies between 3.7–10.0 ppb under four different conditions.

The sensor response times have been reported by two different investigations. Spinelle et al (2015a) reported the t_{90} values for three different sensors as 1.3 min, 1.6 min, and 38.4 min. The abnormally high response time was reported for the CairPol CairClip sensor possibly due to the presence of an ozone filter and/or a humidity buffer in that sensor. The Williams et al (2014c) reported the $t_{lag} < 1$ min and $t_{rise} = 8$ min and 18 min for one sensor under two different conditions.

EC NO_2 sensors are also impacted by interfering gases and environmental conditions. As was discussed previously, EC NO_2 sensors need to be calibrated such that the dependence of their response on the O_3 concentration, temperature, and humidity are taken in account. Mead et al (2013) reported about 100% interference by O_3 on the measurements conducted by NO2-A1 sensor, which effectively means that the sensor is measuring the sum concentration of NO_2 and O_3. Additionally, they reported that interference by NO and CO at ambient conditions is quite low, which is also supported by data from Castell et al (2016) as given in Table 8. The cross-sensitivities to a total of six gases was reported by Spinelle et al (2015a) and Lewis et al (2016) for different EC NO_2 sensors. Spinelle et al (2015a) reported extremely high cross sensitivity to O_3 (1.5 ppb of NO_2 output per ppb of O_3 concentration) for two of the sensors. The other NO_2 sensor tested by them was found to have extremely low cross-sensitivity to O_3 since it contained an O_3

filter at its inlet. Oddly, Lewis et al (2016) reported no cross-sensitivity to O_3 for the sensor tested by them; however, it was likely due to the presence of an O_3 filter. From this cross-sensitivity data, we calculated that the interference by CO, CO_2, NO, NH_3, and SO_2 would cause an estimated uncertainty of -3.3 to 1.3 ppb NO_2 at typical urban ambient concentrations of interfering gases (the estimation procedure was described while discussing the cross-sensitivities of O_3 sensors). The interference to SO_2 was reported by Williams et al (2014c) for one EC NO_2 sensor to be 34.2 ppb of NO_2 for >200 ppb of SO_2. However, typically such high SO_2 concentration would not be encountered in an urban setting, meaning that the influence of SO_2 on the sensor response would be much lower.

The effects of temperature and humidity on EC NO_2 sensor outputs have been reported by a few chamber investigations. Spinelle et al (2015a) found that the sensor response increased by 0.093–0.47 ppb of NO_2 per °C increase in temperature from 12–32 °C for three different EC sensors as given in Table 8. However, Sun et al (2016) did not detect any influence of temperature (15–21°C) on the NO2-B4 sensor's response. Their temperature range is only 6°C, and we can estimate an increase in the sensor output by only 2.8 ppb (based on 0.47 ppb NO_2 per °C, reported by Spinelle et al (2015a)), which was probably left undetected by Sun et al (2016). The impact of humidity on EC sensor outputs was reported to be between -0.057 to 0.13 ppb of NO_2 per percentage point increase in relative humidity (from 40–80% RH) for three different sensors by Spinelle et al (2015a). Sun et al (2016), also found that humidity ranging from 40–70% RH increased the sensor output for the NO2-B4 sensor; however, Lewis et al (2016) did not observe any influence of humidity for the same sensor model. Overall, we find conflicting results regarding the effects of humidity and temperature on the response of low-cost NO_2 sensors, which might be arising due to differences in sensor models and/or manufacturing variations between same sensor types.

The sensor drift was found to be between -0.497 to -0.065 ppb/day for the three different EC NO_2 sensors during six months of chamber testing (Spinelle et al, 2015a). This would cause a decrease in the reported NO_2 concentration by 12–89 ppb during a six month monitoring campaign. Castell et al (2016) also found that the NO2-B4 sensor's behaviour changed significantly during their six months long testing. Clearly, this effect needs to be considered when conducting long-term campaigns with EC NO_2 sensors.

Model	Performance assessment

MICS-2710 (MOS sensor)	Comparison with reference measurements
	Median RMSE was 8.4 ppb (range 6.9–9.5 ppb) during field testing of six sensors for NO_2 concentrations between ~0–70 ppb by using a multiple linear regression equation that accounted for temperature and humidity effects (Piedrahita et al, 2014).
	$R^2 > 0.98$ versus reference during chamber testing in two different conditions (Williams et al, 2014c).
	$R^2 = 0.200$–0.206 and 0.126–0.131 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2015b)
	$R^2 = 0.744$–0.745 and 0.057–0.063 versus reference during calibration and validation phases, respectively, by using multiple linear regression with O_3 concentration and temperature as additional predictors (Spinelle et al, 2015b).
	$R^2 = 0.02$ versus reference (Borrego et al, 2016)
	$R^2 = 0.05$–0.06 versus a FRM/FEM measurements at a regulatory monitoring site in suburban Atlanta, Georgia, USA (Jiao et al, 2016).
	Repeatability
	s = 2.6 ppb and 5.0 ppb during chamber testing in two different conditions (Williams et al, 2014c).
	Reproducibility
	High sensor-to-sensor reproducibility with $R^2 = 0.88$–0.98 (Piedrahita et al, 2014).
	LOD
	LOD = 6.3–10.4 ppb during chamber testing in two different conditions (Williams et al, 2014c).
	Resolution
	Resolution = 0.1–4.1 ppb during chamber testing in four different conditions (Williams et al, 2014c).
	Response time
	t_{lag} = 1 min during chamber testing in two different conditions (Williams et al, 2014c).
	t_{rise} = 21 and 33 min during chamber testing in two different conditions (Williams et al, 2014c).
	Cross-sensitivity
	The sensor showed a response equivalent to 0 ppb NO_2 at > 200 ppb of SO_2 (Williams et al, 2014c).
MICS-4514 (MOS sensor)	Comparison with reference measurements
	$R^2 = 0.168$–0.269 and 0.016–0.203 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2015b).
	$R^2 = 0.525$–0.786 and 0.010–0.016 versus reference during calibration and validation phases, respectively, by using multiple linear regression with

temperature and concentrations of O_3 and NO as additional predictors (Spinelle et al, 2015b).

AGT Environmental Sensor (MOS sensor)	Comparison with reference measurements
	$R^2 > 0.99$ versus reference during chamber testing in four different conditions (Williams et al, 2014c).
	Repeatability
	s = 1.2–7.5 ppb during chamber testing in four different conditions (Williams et al, 2014c).
	LOD
	LOD = 15.3–26.6 ppb during chamber testing in four different conditions (Williams et al, 2014c).
	Resolution
	Resolution = 0.8–6.8 ppb during chamber testing in eight different conditions (Williams et al, 2014c).
	Response time
	t_{lag} = 1 min during chamber testing in four different conditions (Williams et al, 2014c).
	t_{rise} = 5–20 min during chamber testing in four different conditions (Williams et al, 2014c).
	Cross-sensitivity
	The sensor showed a response equivalent to 19.5 ppb NO_2 at > 200 ppb of SO_2 (Williams et al, 2014c).
Alphasense NO2-A1 (EC sensor)	Comparison with reference measurements
	$R^2 > 0.99$ versus calibration gas standard during chamber testing (Mead et al, 2013).
	R^2 = 0.89–0.92 versus TEM 42D NO-NO2-NOx analyser during testing above a busy urban road after accounting for cross sensitivity to O_3 (Mead et al, 2013).
	$R^2 > 0.97$ versus reference during chamber testing in two different conditions (Williams et al, 2014c).
	Repeatability
	s = 4.6 ppb and 23.3 ppb during chamber testing in two different conditions (Williams et al, 2014c).
	Reproducibility
	High sensor-to-sensor reproducibility with R^2 = 0.94–0.95 (Mead et al, 2013).
	LOD
	1 ppb (Mead et al, 2013).
	11.6–29.4 ppb during chamber testing in two different conditions (Williams et al, 2014c).
	Resolution

Resolution = 3.7–10.0 ppb during chamber testing in four different conditions (Williams et al, 2014c).

Cross-sensitivity

To O_3: ~100% of measured NO_2 at typical ambient O_3 concentrations (Mead et al, 2013).

To CO: –0.02 ± 0.03% of measured NO_2 at typical ambient CO concentration (Mead et al, 2013).

To NO: +1.2 ± 0.11% of measured NO_2 at typical ambient NO concentration (Mead et al, 2013).

The sensor showed a response equivalent to 34.2 ppb NO_2 at >200 ppb of SO_2 (Williams et al, 2014c).

Response time

t_{lag}< 1 min during chamber testing in two different conditions (Williams et al, 2014c).

t_{rise} = 8 min and 18 min during chamber testing in two different conditions (Williams et al, 2014c).

CairPolCairClip NO2 ANA (EC sensor)	Comparison with reference measurements $R^2 > 0.99$ during chamber testing (Spinelle et al, 2015a). $R^2 = 0.24–0.46$ and 0.004–0.04 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2015b) $R^2 = 0.58–0.74$ and 0.004–0.02 versus reference during calibration and validation phases, respectively, by using multiple linear regression with O_3 concentration as an additional predictor (Spinelle et al, 2015b). Repeatability s = 1.7 ppb at 100 ppb NO_2 (Spinelle et al, 2015a). LOD 0.9 ppb (Spinelle et al, 2015a). Response time t_{90} = 38.4 min (Spinelle et al, 2015a). Cross sensitivity (in ppb/ppm for CO and CO_2 and ppb/ppb for other gases) –0.010 to O_3, –0.007 to NO, –0.001 to CO, 0.009 to CO_2, and –0.032 to NH_3 (Spinelle et al, 2015a). Dependence on humidity/temperature Response changed by –0.057 ppb of NO_2 per percentage point increase in relative humidity from 40-80% RH (Spinelle et al, 2015a). Response changed by 0.093 ppb of NO_2 per °C increase in temperature from 12–32°C (Spinelle et al, 2015a). Drift < –0.065 ppb/day during six months of chamber testing (Spinelle et al, 2015a).

Alphasense NO2-B4 (EC sensor)	Comparison with reference measurements
	$R^2 > 0.99$ during chamber testing (Spinelle et al, 2015a).
	$R^2 = 0.11$–0.23 and 0.002–0.009 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2015b)
	$R^2 = 0.35$–0.68 and 0.026–0.086 versus reference during calibration and validation phases, respectively, by using multiple linear regression with O_3 concentration, temperature, and RH as additional predictors (Spinelle et al, 2015b).
	$R^2 = 0.06$–0.89 versus reference measurements when tested as parts of four different sensor platforms (Borrego et al, 2016)
	$R^2 > 0.99$ versus Teledyne T500U NO_2 monitor during chamber testing (Sun et al, 2016).
	$R^2 = 0.90$ versus a regulatory grade monitor after applying a humidity correction algorithm during testing near a roadside (Sun et al, 2016).
	$R^2 = 0.96$–0.99 versus reference measurements during chamber testing (Castell et al, 2016).
	$R^2 = 0.04$–0.27 versus reference measurements during testing as part of 24 identical AQMesh platforms at an air quality monitoring station in Norway (Castell et al, 2016).
	Repeatability
	$s = 2.9$ ppb at 100 ppb NO_2 (Spinelle et al, 2015a).
	$s = 2.8$ ppb at 100 ppb NO_2 (Castell et al, 2016).
	LOD
	8.6 ppb (Spinelle et al, 2015a).
	6 ppb (Sun et al, 2016).
	2.7 (Castell et al, 2016).
	Response time
	$t_{90} = 1.3$ min (Spinelle et al, 2015a).
	Cross sensitivity (in ppb/ppm for CO and CO_2 and ppb/ppb for other gases)
	1.5 to O_3, -0.032 to NO, $<-1.3 \times 10^{-3}$ to CO, -0.042 to CO_2, and -0.089 to NH_3 (Spinelle et al, 2015a).
	0.00 to O_3, -0.054 to NO, 0.00 to CO, 1.5×10^{-1} to CO_2, and 0.027 to SO_2, estimated from Lewis et al (2016).
	No cross-sensitivity to O_3 (due to presence of an ozone filter), NO, and CO (Castell et al, 2016).
	Dependence on humidity/temperature
	Response changed by 0.13 ppb of NO_2 per percentage point increase in relative humidity from 40-80% RH (Spinelle et al, 2015a).
	Response changed by 0.47 ppb of NO_2 per °C increase in temperature from 12-32°C (Spinelle et al, 2015a).

Sensor's response increased as the humidity was increased from 40% to 70% RH (Sun et al, 2016).

Sensor's response not affected by temperature ranging from 15–21°C (Sun et al, 2016).

Response changed by 0.00 ppb of NO_2 per % point RH increase in humidity, estimated from Lewis et al (2016).

Sensor stability

<–0.497 ppb/day during six months of chamber testing (Spinelle et al, 2015a).

Significant change in sensor behaviour during the six months of testing (Castell et al, 2016).

Citytech NO2_3E50 (EC sensor)	Comparison with reference measurements
	R^2 > 0.99 during chamber testing (Spinelle et al, 2015a).
	R^2 = 0.001–0.002 and 0.051–0.068 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2015b)
	R^2 = 0.56–0.77 and 0.062–0.078 versus reference during calibration and validation phases, respectively, by using multiple linear regression with O_3 concentration, temperature, and RH as additional predictors (Spinelle et al, 2015b).
	R^2 = 0.89 versus reference (Borrego et al, 2016)
	Repeatability
	s = 0.8 ppb at 100 ppb NO_2 (Spinelle et al, 2015a).
	LOD
	0.5 ppb (Spinelle et al, 2015a).
	Response time
	t_{90} = 1.6 min (Spinelle et al, 2015a).
	Cross sensitivity (in ppb/ppm for CO and CO_2 and ppb/ppb for other gases)
	1.5 to O_3, –0.058 to NO, –1.6×10^{-3} to CO, –0.013 to CO_2, and –0.11 to NH_3 (Spinelle et al, 2015a).
	Dependence on humidity/temperature
	Response changed by 0.062 ppb of NO_2 per percentage point increase in relative humidity from 40-80% RH (Spinelle et al, 2015a).
	Response changed by 0.16 ppb of NO_2 per °C increase in temperature from 12-32°C (Spinelle et al, 2015a).
	Drift
	<–0.196 ppb/day during six months of chamber testing (Spinelle et al, 2015a).

Table 8: Performance characteristics of low-cost NO_2 sensors.

3.2.4 NO Sensors

Three EC NO sensors have been tested by scientific investigations as given in Table 9. Mead et al (2013) reported good R^2 coefficients ($R^2 > 0.99$) with the reference measurements during chamber testing of the NO-A1 sensor. They also reported good R^2 values ($R^2 = 0.80–0.95$) during measurements of roadside NO concentration, when the sensors were located indoors and exposed to very minimal temperature variations. However, when they placed the sensors outside, the baseline response of the sensors was found to be affected by the ambient temperature with a strong exponential dependence. Similar sensor characteristics were also reported by (Popoola et al, 2016), who observed a strong exponential relationship ($R^2 = 0.9$) between the sensor's baseline response and temperature. Once the sensor's baseline response was corrected for temperature effects, it led to significant improvement in R^2 (from 0.02 to 0.71–0.78) against reference measurements (Popoola et al, 2016). Thus, it seems crucial to account for the impact of temperature on the NO-A1 sensor before making measurements.

For the Alphasense NO-B4 sensors, Borrego et al (2016) has reported the R^2 values as 0.34 and 0.80, when it was tested as part of two different platforms. The reason for this discrepancy could be the difference in signal processing algorithms used for processing the raw sensor output by the two platforms. Once again, this suggests the need for properly calibrating the sensors by accounting for the different factors that might influence their response before using them. Castell et al (2016) reported $R^2 = 0.99$ during chamber testing for the NO-B4 sensors. However, they reported variable R^2 values ($R^2 = 0.36–0.96$ as given in Table 9) during field testing, probably arising due to manufacturing variations in the sensors and/or sensor platforms.

Spinelle et al (2017) reported the R^2 values for the Citytech NO_3E100 sensor under laboratory and field conditions. The laboratory performance was excellent ($R^2 > 0.99$); however, the performance under real-world conditions was extremely poor with no association found between the sensor response and the reference measurements. One possible reason could be a faulty sensor; however, further investigations are required to investigate the NO_3E100 sensor's performance under field conditions.

Good repeatability and reproducibility was observed for the NO-A1 and NO-B4 sensors, respectively (Table 9). The LOD values reported are 2.4 and 4 ppb for the NO-A1 and NO-B4 sensors, respectively, and 74.9 ppb for the NO_3E100 sensor (see Table 9). Once again it seems that the NO_3E100 sensor was faulty given its unreasonably high LOD.

The cross-sensitivities for the NO-A1 sensor to CO and NO_2 are quite small with its response increasing by about 0.10–0.45% of NO at typical ambient concentrations of the interfering gases (Mead et al, 2013). Similarly, Castell et al (2016) reported no effect of cross-sensitivities to O_3, NO_2, and CO on NO-B4 sensor's output. The cross-sensitivities reported by Spinelle et al (2017) and Lewis et al (2016) for the two different EC NO sensors are given in Table 9. We computed the impact of those cross-sensitivities on the sensor outputs by multiplying the cross-sensitivity values with the corresponding concentrations of interfering gases. For NO_2, O_3, CO and SO_2 concentrations, we used the EU specified limits. We used a representative value for background urban sites for CO_2 (400 ppb) and NH_3 (30 ppb). For the NO-B4 sensor, the estimated change is response was negligible (–0.6 to 0.6 ppb of NO) due to interferences by O_3, CO, CO_2, and SO_2; however, NO_2 interference would cause a large decrease (22.1 ppb of NO) in the measured concentration of NO. This seems contradictory to the conclusions obtained by Castell et al (2016) for the cross-sensitivity of the NO-B4 sensor to NO_2. However, it should be noted that the sensors tested by Castell et al (2016) were part of the AQMesh platform, which uses proprietary algorithms to compensate for cross-sensitivity effects. For the NO_3E100 sensors, it was found that the sensor response would change by –11.4 ppb, –5.0 ppb, 0.0 ppb, 4.8 ppb, and 19.0 ppb due to interferences by NH_3, O_3, CO_2, NO_2, and CO, respectively. Thus, depending on the sensor model, the gaseous interferences should be considered while making NO measurements.

The strong influence of temperature on the NO-A1 sensor was discussed previously. Similarly, Spinelle et al (2017) reported a significant dependence of the NO_3E100 sensor's response on the temperature (the response changed by –1.05 ppb of NO per °C increase in temperature). However, they also found that the dependence on humidity for this sensor was very small as given in Table 9. Furthermore, Popoola et al (2016) reported that there was no significant change in the sensitivity of this sensor for a period of one year. For the NO-B4 sensor, we estimated that its response would be strongly influenced by the relative humidity by using the data reported by Lewis et al (2016). Thus, the discrepancy between the reported influences of relative humidity the NO-A1 and NO-B4 sensors' responses needs further investigation.

Model	Performance assessment
AlphasenseNO-A1 (EC sensor)	Comparison with reference measurements R^2 > 0.99 versus calibration gas standard during chamber testing (Mead et al, 2013).

R^2= 0.80–0.95 versus a chemiluminescence analyser during testing above a busy urban road with the sensor placed indoors (Mead et al, 2013).

R^2 improved from 0.02 to 0.71–0.78 versus a chemiluminescence analyser after correcting for sensor's baseline dependence on temperature (Popoola et al, 2016).

LOD

4 ppb (Mead et al, 2013).

Cross-sensitivity

To CO: +0.10 ± 0.08% of measured NO at typical ambient CO concentration (Mead et al, 2013).

To NO_2: +0.45 ± 0.2% of measured NO at typical ambient NO_2 concentration (Mead et al, 2013).

Reproducibility

High sensor-to-sensor reproducibility with R^2 = 0.84–0.97 (Mead et al, 2013).

Dependence on temperature

Baseline response showed a strong exponential dependence (R^2 = 0.9) on temperature ranging from 0–36°C (Popoola et al, 2016).

Long term performance

No statistically significant change in temporal sensitivity for a one year period (Popoola et al, 2016).

AlphasenseNO-B4 (EC sensor)	Comparison with reference measurements

R^2 = 0.34 and 0.80 versus reference measurements when tested as parts of two different sensor nodes (Borrego et al, 2016).

R^2 = 0.99 versus reference measurements during chamber testing (Castell et al, 2016).

R^2 = 0.36–0.96 versus reference measurements during testing as part of 24 identical AQMesh platforms at an air quality monitoring station in Norway (Castell et al, 2016).

LOD

2.4 (Castell et al, 2016).

Repeatability

s = 1.5 ppb at 100 ppb NO (Castell et al, 2016).

Cross sensitivity (in ppb/ppb for all gases)

−1.057 to NO_2, −0.020 to O_3, 0.00 to CO, 3.2×10^{-5} to CO_2, and 0.013 to SO_2, estimated from Lewis et al (2016).

No cross-sensitivity to O_3, NO_2, and CO (Castell et al, 2016).

Dependence on humidity

Response changed by −0.543 ppb of NO per percentage point increase in relative humidity, estimated from Lewis et al (2016).

	Long term performance
	Significant change in sensor behaviour during the six months of testing (Castell et al, 2016).
Citytech NO_3E100 (EC sensor)	Comparison with reference measurements
	$R^2 = 2.3 \times 10^{-5} – 5.7 \times 10^{-3}$ and 0.001–0.018 versus reference during calibration and validation phases, respectively, by using simple linear regression (Spinelle et al, 2017).
	$R^2 = 1.8 \times 10^{-3} – 7.5 \times 10^{-2}$ and 0.009–0.020 versus reference during calibration and validation phases, respectively, by using multiple linear regression with RH and T as additional predictors (Spinelle et al, 2017).
	$R^2 > 0.99$ versus reference during chamber testing at 22°C and 60% RH (Spinelle et al, 2017).
	LOD
	74.9 ppb (Spinelle et al, 2017).
	Dependence on temperature
	Response changed by –1.05 ppb of NO per °C increase in temperature from 7–37°C (Spinelle et al, 2017).
	Dependence on humidity
	Response changed by 0.041 ppb of NO per percentage point increase in RH from 40-80% (Spinelle et al, 2017).
	Cross sensitivity (in ppb/ppm for CO and CO_2 and ppb/ppb for other gases)
	–0.16 to O_3, 0.23 to NO_2, 2.2 to CO, 2.6×10^{-3} to CO_2, and –0.38 to NH_3 (Spinelle et al, 2017).

Table 9: Performance characteristics of low-cost NO sensors

4 Beyond the State of the Art

To successfully achieve the aims of a low-cost sensor-based air pollution monitoring system, it is crucial to involve citizens through a 'crowd sourced' effort as defined by Thompson (2016). Such an effort would typically comprise of a pollutant sensor interfaced wirelessly with a smartphone providing pollution data to the user and a central server. By involving citizens as enablers and users of the sensing system, several goals can be readily achieved, which include developing local pollutant maps, assessing individual exposures, and increasing citizens' awareness about air pollution. However, challenges with respect to maintaining user engagement and sensor performance need to be addressed before such crowd-sourced campaigns can be widely adopted.

Another challenge faced in deploying sensors at a large scale is related to quality control of the data. While many scientific studies have utilized low-cost PM and gaseous sensors in a variety of

air pollution monitoring activities, only a few have reported sensor performance characteristics and the associated data quality. To further exacerbate the matter, performance assessments have been done by using different experimental setups, reference equipment, and environmental conditions, making it infeasible to compare them with each other and draw generalized conclusions regarding the data quality. Thus, in order to deploy a large-scale sensor network and meaningfully use the plethora of data generated, it is imperative to formulate standard guidelines for assessing the short and long term performance of low-cost sensors, which can be used by one and all.

Improper sensor calibration seems to be a major issue plaguing the data quality. The sensor response is largely impacted by environmental conditions, particle characteristics (for PM sensors), and gaseous cross-sensitivities (for gas sensors). Thus, calibration methods that don't include these factors are bound to produce erroneous data. The sensor manufacturer (or user) should first generate a calibration equation by using laboratory testing, and identify the major factors that affect the sensor's response. The calibration curve can then be improved by the user through testing the sensor under actual conditions of deployment. Advanced calibration techniques such as neural networks could also be considered since they might be more effective than regression modelling.(De Vito et al, 2008; De Vito et al, 2009; De Vito et al, 2015; Esposito et al, 2016; Spinelle et al, 2015b; 2017)

5 Recommendations for the Work Package

5.1 PM Sensors

Various low-cost PM sensors are available in the market (Table 1) that measure the concentration of particles based on the amount of light scattered by them when illuminated by a light source. This method is suitable only for measuring particles larger than ~0.3 μm in diameter since smaller particles don't scatter enough light. To use this technique for measuring $PM_{2.5}$ or PM_{10}, it should be ensured that the sensor is equipped with an impactor or filter at the air inlet that provides the appropriate cut-off diameter (2.5 μm and 10 μm for measuring $PM_{2.5}$ and PM_{10}, respectively). This feature is not provided in any of the sensors given in Table 2, expect for the Sharp DN7C3CA006 sensor that is equipped with a 2.5 μm virtual impactor. A few sensors such as the Dylos utilize signal processing algorithms to categorize particles between $PM_{2.5}$ and PM_{10}; however, such algorithms may lead to significant misclassification (Sousan et al, 2016b).Thus, to measure

concentrations of $PM_{2.5}$ or PM_{10}, any of the sensors given in Table 2 can be used in principle by combining the sensor with an appropriate size-selection mechanism, if not already provided by the manufacturer.

There exist several investigations that have already used these sensors for a variety of air pollution monitoring applications. However, there are very few studies that have assessed the performance of these sensors, which makes it difficult to make generalized recommendations about selecting or not selecting a particular sensor. Our survey of scientific literature found that only three sensors (Sharp GP2Y1010AU0F, Shinyei PPD42NS, and Dylos) have been tested by five or more studies. The performance characteristics of these three sensors are roughly similar as shown in Table 4. The sensors generally demonstrate good comparison with reference measurements and reasonable precision. However, their outputs are highly dependent on the particle composition and size and relative humidity, meaning that they should be carefully calibrated before using them. Thus, from a performance perspective, any of these three sensors can be used for monitoring PM as part of this project.

However, it is important to note that the GP2Y1010AU0F and PPD42NS sensors are available as stand-alone sensors, and need to be integrated into a data acquisition and storage system; whereas the Dylos has its own data acquisition, storage, and display system. This is also one of the reasons for the much higher cost of Dylos as compared to the other two sensors. For this project, since we already have an in-house data acquisition and storage system, the higher cost of Dylos is not justified. Thus, the GP2Y1010AU0F and PPD42NS sensors are suitable from a cost perspective.

Overall, the Sharp DN7C3CA006 sensor seems to be a good choice for measuring $PM_{2.5}$ concentration since it comes equipped with a 2.5 μm virtual impactor, and also has a low cost. For measuring PM_{10}, we recommend using either the Sharp GP2Y1010AU0F or the Shinyei PPD42NS sensor since both have reasonable performance characteristics combined with a low cost. Note that the raw output of these PM sensors would roughly correspond to PM_{10} concentration since particles greater than 10 μm are difficult to draw in the sensing zone, meaning there should not be a need for any impactor/filter at the inlet.

5.2 Gas sensors

Two types of low-cost sensors are available for measuring various gases; MOS sensors and EC sensors. We discussed the broad characteristics of each sensor types in section 3.2. One important distinguishing factor between them is the cost, which are about ten dollars for the MOS sensors and about hundred dollars for the EC sensors. Thus, clearly from a cost perspective MOS sensors are much more suitable for this project than EC sensors. However, the performance characterization also needs to be accounted before making recommendation for a particular sensing technology for measuring a particular gas. This assessment is given in the following subsections.

5.2.1 CO sensors

As discussed in Section 3.2.1, a very limited number of investigations have tested the performance of the different EC and MOS CO sensors. A few discrepancies between these studies were found related to the performance characterization of different sensors, which could be attributed to the different sensor designs and/or the different test conditions and methods used by the different investigators. Thus, in order to access the performance traits of these CO sensors for air pollution monitoring application, further investigations are required. Nevertheless, for this project, we recommend the MOS CO sensors because on their low-cost as compared to the EC sensors.

5.2.2 O_3 sensors

The different MOS sensors had reasonably good performance under both chamber and real-world conditions with the R^2 correlation coefficients typically ranging from 0.77–0.94, except for the MICS-2610 sensor which reportedly had a low correlation coefficient and high residual values. The EC sensors reportedly had excellent R^2 ($R^2 > 0.99$) correlation coefficients with reference measurements when tested under chamber conditions; however, under field conditions, they reportedly had variable R^2 values ranging from 0.021–0.94. Unfortunately, there are not enough studies in the literature that have tested the EC O_3 sensors, meaning that their performance assessment cannot be judged properly at this stage. Thus, it is recommended to use MOS sensors over EC sensors for O_3 since they seem to offer reasonably good performance at a very cheap price. It is not feasible to make recommendation about any particular MOS O_3 sensor due to the lack of data about performance assessment; however, Table 7 and Section 3.2.2.1 should be carefully consulted before purchasing and deploying a MOS O_3 sensor.

5.2.3 NO$_2$ sensors

The performance characteristics of three MOS and four EC NO$_2$ sensors were reported in Section 3.2.3. Once again, the laboratory performance of these sensors is excellent with the R^2 correlation coefficients with reference measurements being typically greater than 0.9. However, under field conditions, both sensor types have significantly deteriorated performances (R^2 < 0.2 typically). In order to use either of these sensor types, it is necessary to account for the impact of O$_3$, NO, temperature, humidity, and aging as noted by several investigation that reported reasonable R^2 values (R^2 = 0.4–0.9) with respect to reference measurements. The interference by O$_3$ is mainly problematic and needs to be accounted for either by using an O$_3$ filter at the inlet or through a correction algorithm. The other performance metrics as given in Table 8 don't seem to suggest any significant advantage in using the EC NO$_2$ sensors over the MOS sensors, meaning that the higher cost of the former is probably unjustified for this project.

Out of the three MOS NO$_2$ sensors given in Table 8, the AGT Environmental sensor has only been tested in chamber conditions. For the MICS-2710 sensor, some real-world investigations have tested its performance, but their results are conflicting. This discrepancy is likely caused due to the sensor's output being affected by interfering gases and environmental conditions, which were probably not accounted by studies that have reported poor performance by this sensor. Thus, this sensor might provide reasonable measurements of NO$_2$, provided it is calibrated carefully and frequently, to account for factors that affect its response as discussed previously. However, the sensor model has been discontinued, and the upgraded version is the MICS-2714. For the MICS-2714 sensor, performance assessment has been done by only one study as reported in Table 8 under the name MICS-4514, which is actually a combined version of a MICS-2714 NO$_2$ sensor and a MICS-5524 CO sensor. We don't have any reason to believe that the performance of the new MICS-2714 will be significantly worse than the MICS-2710 sensor. Thus, the MICS-2714 sensor is recommended for this project.

5.2.4 NO sensors

Only a limited number of investigations have tested the performances of different EC NO sensors as discussed in Section 3.2.4. We could not perform assessment of MOS NO sensors in our literature review; however, the development of such sensors is underway (Fine et al, 2010). Based on the very limited data available, it appears that the Aphasense NO sensors might be suitable for NO monitoring.

5.3 Calibration Procedure for iSCAPE Sensors

Two sensors solutions, Low-cost citizen sensors and High-end living lab sensors have been developed for iSCAPE project. Low-Cost Sensor, is aimed at providing a low-cost environmental sensor solution non-technical users can easily deploy. The design developed for the project is a complete reiteration of the Smart Citizen Kit, a piece of hardware for citizen sensing already tested in other projects for more than five years. High-End Sensors, is aimed at providing the Living Labs with a system for monitoring the performance of their interventions. The Station aims at providing a solution that can be used by the Living Labs not just from a scientific point of view but also as a tool to engage local communities on air pollution related issues. Further detailed information is avalible on iSCAPE website. https://docs.iscape.smartcitizen.me/. Based on literature, we have developed detailed calibration procedure and documented as separate deliverable: D3.13 Comprehensive release High-end and low-cost sensing platforms. Comprehensive calibration protocol is documented on https://docs.iscape.smartcitizen.me/Sensor%20Analysis%20Framework/. A brief overview of calibration is provided in the following sections.

5.3.1 Principles

The sensor calibration procedure for the iSCAPE sensor solution can be split into three stages: (1) Behaviour assessment: Base testing for assessing general sensor response, stabilisation time or operational modes. Pulse mode operation is also explored in this stage for energy saving purposes. (2)Characterisation: Assess generic sensor parameters sensitivity, zero and span. (3) Modelisation: Include other variables such as environmental factors and sensor cross-sensitivity. Each of these stages apply differently depending on the type of sensor, for instance the electrochemical sensors present in the Station are already characterised by the manufacturer, while the Metal Oxide Sensors in the Urban Board of the Citizen Kit are not. The different characteristics of these sensors make different calibration approaches to be carried out. An initial behaviour assessment is to be carried out in laboratory conditions in order to determine the optimal operational modes. This includes basic parameters such as sensor response, heating time and temperature as well as more advanced ones such as heating pulse mode operation. For this purpose, a portable, open source, reproducible test cell has been developed for controlled testing with a web based acquisition interface. Secondly, base calibration parameters need to be determined in controlled conditions. In this stage, the aim would be to find parameters such as:

- Sensor sensitivity: the sensor response per each ppm of target pollutant in nominal conditions
- Zero: the sensor reading in zero air (pure air at 25ºC)
- Sensor response (t90)
- Sensor range: maximum and minimum readings for the sensor

Finally, after this initial calibration assessment, it is critical to gather as much data as possible from long term sensor deployments. These deployments should aim to cover the widest range of sensor exposure conditions, in order to generate robust models. While dealing with low cost sensors this stage is very important, as it is detailed in the sections below. These sensor deployments serve for two main purposes: to generate quantitative classification methods that can classify the air quality in predefined ranges (i.e. 'poor', 'fair', good'); and to generate predictive qualitative models for more accurate values. Either of them need large amounts of data if the models are aimed to be representative. Additionally, by the mere nature of the data and the sensors themselves, these models would need to be capable of: Robust to noise, learn non-linear relationships, multivariate inputs and learned temporal dependence. These needs make machine learning methods great candidates for modelling the data. Traditionally, time series forecasting has been dominated by linear methods because they are well understood and effective on many simpler forecasting problems. However, deep learning neural networks are able to automatically learn arbitrary complex mappings from inputs to outputs and support multiple inputs and outputs. Therefore, deep learning methods such as MLPs and LSTMs offer a lot of promise for the type of problem presented in the iSCAPE project. The combination of these algorithms with large amounts of data gathered during the iSCAPE project offers a great opportunity to demonstrate the use of low cost sensors for air quality monitoring.

These deployments should at least guarantee the following needs: (i)A checked reference measurement for the sensors to be compared against it, (ii)sufficient sensor stabilisation time and varied operational conditions, and (iii)careful monitoring of the sensor correct operation: connectivity and power supply, among others.

5.3.2 Metal Oxide Sensors

Due to their construction, low cost metal oxide sensors suffer from high levels of spread for their baseline resistance and sensitivity. As well, these sensors are generally reactive to other pollutants in the atmosphere, with low selectivity of the actual target pollutant and drifts in their

behaviour can be seen after some weeks of exposure. Therefore, metal oxide sensors require a careful characterisation and medialisation in both, laboratory and open air conditions. Furthermore, metal oxide sensors show short and long term drifts in their calibrations. For this reason, a recursive calibration approach is proposed. This procedure would comprise:

| Laboratory Characterisation | → | Sensor Collocation | → | Deployment And Behaviour Monitoring | → | Sensor Re-assessment |

1. Sensor characterisation in laboratory conditions to assess sensitivity, baseline resistances sensor-to-sensor spread, aiming to obtain normalising factors for each sensor or group of sensors

2. Sensor collocation with reference equipment for model development, accounting for the laboratory factors obtained in the previous stage and in order to include more complex environmental factors

3. Sensor deployment stage with independent measurement

4. Sensor re-assessment by either laboratory characterisation or collocation with reference equipment. This could serve for correction for the model parameters used during the deployment and to assess the sensor reliability and need for replacement

Further to the sensor re-assessment, other deployments could be explored should there not be sensor breakdown.

5.3.3 Electrochemical Sensors

The electrochemical sensor manufacturer keeps a database of the sensor sensitivities and zero currents (baseline response) of each individual sensor. Therefore, the calibration approach for the electrochemical sensors is reduced to an in-field validation of their behaviour and a model proposal that is described in the electrochemical sensor baseline methodology. Surely, further models developed after long term data collection with field deployments are to be considered in order to improve sensor readings.

5.3.4 PM Sensors

The selected PM sensor is as well, characterised by the manufacturer and it provides an accurate measurement with its calibration. As with the above mentioned electrochemical sensors, a long term field deployment with reference equipment is to considered in order to develop more complex models including environmental features such as humidity, which has been demonstrated to have an influence on PM readings.

6 Conclusions

This report presents a review of the state-of-the-art of low-cost sensors/sensing-technologies for measuring particulate and gaseous air pollutants based on up-to-date scientific literature with a focus on providing guidance to end users for sensor selection. Based on this review, following conclusions can be drawn:

- To measure $PM_{2.5}$ and PM_{10}, several low-cost optical sensors are available in the market. The low-cost sensors tend to perform reasonably well as compared to conventionally used particle monitors of significantly higher cost. However, the sensors need to carefully calibrated under specific test conditions (i.e., the iSCAPE city sites) before usage since changes in environmental conditions and particle characteristics can drastically change their response.

- To measure gaseous air pollutants such as O_3, NO_2, CO, and NO; two types of low-cost sensors are generally available in the market: (i) MOS based sensors and (ii) EC based sensors. The performance characteristics of these gaseous sensors were variable with some investigations reporting good agreement with reference measurements and some reporting otherwise. This discrepancy was attributed to the differences in the signal processing algorithms and test conditions/methods used in different studies. Nevertheless, it is clear that these sensors need careful and frequent calibration such that the various factors that influence their response are accounted/controlled before usage.

- It was found that the EC sensors are typically more expensive than MOS sensors, but the EC sensors are claimed to have better performance characteristics. However, we did not find enough evidence of significant performance benefits in using EC sensors over MOS sensors to justify their higher costs. Thus, MOS based sensors were recommended for

monitoring O_3, NO_2, and CO. An EC based sensor was recommended for monitoring NO since MOS NO sensors are not currently available in the market.

7 References

Aleixandre, M. & Gerbolesb, M. (2012) Review of Small Commercial Sensors for Indicative Monitoring of Ambient Gas. *Chemical Engineering Transactions*, 30.

Alvarado, M., Gonzalez, F., Fletcher, A. & Doshi, A. (2015) Towards the Development of a Low Cost Airborne Sensing System to Monitor Dust Particles after Blasting at Open-Pit Mine Sites. *Sensors (Basel)*, 15(8), 19667-87.

Austin, E., Novosselov, I., Seto, E. & Yost, M. G. (2015) Laboratory Evaluation of the Shinyei PPD42NS Low-Cost Particulate Matter Sensor. *PLoS One*, 10(9), e0137789.

Bhanarkar, M. K., Godase, S. M., Korake, P. M. & Navarkhele, V. V. (2016) Review on WSN Based Outdoor Air Pollution Monitoring System. *International Journal Series in Engineering Science (IJSES)(ISSN: 2455-3328)*, 1-13.

Borrego, C., Costa, A. M., Ginja, J., Amorim, M., Coutinho, M., Karatzas, K., Sioumis, T., Katsifarakis, N., Konstantinidis, K., De Vito, S., Esposito, E., Smith, P., André, N., Gérard, P., Francis, L. A., Castell, N., Schneider, P., Viana, M., Minguillón, M. C., Reimringer, W., Otjes, R. P., von Sicard, O., Pohle, R., Elen, B., Suriano, D., Pfister, V., Prato, M., Dipinto, S. & Penza, M. (2016) Assessment of air quality microsensors versus reference methods: The EuNetAir joint exercise. *Atmospheric Environment*, 147, 246-263.

Castell, N., Dauge, F. R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D. & Bartonova, A. (2016) Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environ Int*.

Castell, N., Viana, M., Minguillón, M. C., Guerreiro, C. & Querol, X. (2013) Real-world application of new sensor technologies for air quality monitoring. *ETC/ACM Technical Paper*, 16.

De Vito, S., Massera, E., Piga, M., Martinotto, L. & Di Francia, G. (2008) On field calibration of an electronic nose for benzene estimation in an urban pollution monitoring scenario. *Sensors and Actuators B: Chemical*, 129(2), 750-757.

De Vito, S., Piga, M., Martinotto, L. & Di Francia, G. (2009) CO, NO2 and NOx urban pollution monitoring with on-field calibrated electronic nose by automatic bayesian regularization. *Sensors and Actuators B: Chemical*, 143(1), 182-191.

De Vito, S., Veneri, P. D., Esposito, E., Salvato, M., Bright, V., Jones, R. & Popoola, O. (2015) Dynamic multivariate regression for on-field calibration of high speed air quality chemical multi-sensor systems, *AISEM Annual Conference, 2015 XVIII*. IEEE.

DEFRA (2011) *https://uk-air.defra.gov.uk/networks/ (accessed 31 October 2016)*, 2011. Available online: [Accessed.

Duvall, R. M., Long, R. W., Beaver, M. R., Kronmiller, K. G., Wheeler, M. L. & Szykman, J. J. (2016) Performance Evaluation and Community Application of Low-Cost Sensors for Ozone and Nitrogen Dioxide. *Sensors (Basel)*, 16(10).

Esposito, E., De Vito, S., Salvato, M., Bright, V., Jones, R. L. & Popoola, O. (2016) Dynamic neural network architectures for on field stochastic calibration of indicative low cost air quality sensing systems. *Sensors and Actuators B: Chemical*, 231, 701-713.

Fenger, J. (2009) Air pollution in the last 50 years–From local to global. *Atmospheric Environment*, 43(1), 13-22.

Fine, G. F., Cavanagh, L. M., Afonja, A. & Binions, R. (2010) Metal oxide semi-conductor gas sensors in environmental monitoring. *Sensors (Basel)*, 10(6), 5469-502.

Gao, M., Cao, J. & Seto, E. (2015) A distributed network of low-cost continuous reading sensors to measure spatiotemporal variations of PM2.5 in Xi'an, China. *Environ Pollut*, 199, 56-65.

Han, I., Symanski, E. & Stock, T. H. (2016) Feasibility of Using Low-cost Portable Particle Monitors for Measurement of Fine and Coarse Particulate Matter in Urban Ambient Air. *J Air Waste Manag Assoc*.

Heimann, I., Bright, V. B., McLeod, M. W., Mead, M. I., Popoola, O. A. M., Stewart, G. B. & Jones, R. L. (2015) Source attribution of air pollution by spatial scale separation using high spatial density networks of low cost air quality sensors. *Atmospheric Environment*, 113, 10-19.

Holstius, D. M., Pillarisetti, A., Smith, K. R. & Seto, E. (2014) Field calibrations of a low-cost aerosol sensor at a regulatory monitoring site in California. *Atmospheric Measurement Techniques*, 7(4), 1121-1131.

Hu, S.-C., Wang, Y.-C., Huang, C.-Y. & Tseng, Y.-C. (2011) Measuring air quality in city areas by vehicular wireless sensor networks. *Journal of Systems and Software*, 84(11), 2005-2012.

Jiang, Q., Kresin, F., Bregt, A. K., Kooistra, L., Pareschi, E., Van Putten, E., Volten, H. & Wesseling, J. (2016) Citizen sensing for improved urban environmental monitoring. *Journal of Sensors*, 2016.

Jiang, Y., Li, K., Tian, L., Piedrahita, R., Yun, X., Mansata, O., Lv, Q., Dick, R. P., Hannigan, M. & Shang, L. (2011) MAQS: a personalized mobile sensing system for indoor air quality monitoring, *Proceedings of the 13th international conference on Ubiquitous computing*. ACM.

Jiao, W., Hagler, G., Williams, R., Sharpe, R., Brown, R., Garver, D., Judge, R., Caudill, M., Rickard, J. & Davis, M. (2016) Community Air Sensor Network (CAIRSENSE) project: evaluation of low-cost sensor performance in a suburban environment in the southeastern United States. *Atmospheric Measurement Techniques*, 9(11), 5281-5292.

Jovašević-Stojanović, M., Bartonova, A., Topalović, D., Lazović, I., Pokrić, B. & Ristovski, Z. (2015) On the use of small and cheaper sensors and devices for indicative citizen-based monitoring of respirable particulate matter. *Environmental Pollution*, 206, 696-704.

Kelly, K. E., Whitaker, J., Petty, A., Widmer, C., Dybwad, A., Sleeth, D., Martin, R. & Butterfield, A. (2017) Ambient and laboratory evaluation of a low-cost particulate matter sensor. *Environ Pollut*, 221, 491-500.

Koehler, K. A. & Peters, T. M. (2015) New Methods for Personal Exposure Monitoring for Airborne Particles. *Curr Environ Health Rep*, 2(4), 399-411.

Kumar, P., Martani, C., Morawska, L., Norford, L., Choudhary, R., Bell, M. & Leach, M. (2016a) Indoor air quality and energy management through real-time sensing in commercial buildings. *Energy and Buildings*, 111, 145-153.

Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., Bell, M., Norford, L. & Britter, R. (2015) The rise of low-cost sensing for managing air pollution in cities. *Environ Int*, 75, 199-205.

Kumar, P., Skouloudis, A. N., Bell, M., Viana, M., Carotta, M. C., Biskos, G. & Morawska, L. (2016b) Real-time sensors for indoor air monitoring and challenges ahead in deploying them to urban buildings. *Sci Total Environ*, 560-561, 150-9.

Lewis, A. C., Lee, J. D., Edwards, P. M., Shaw, M. D., Evans, M. J., Moller, S. J., Smith, K. R., Buckley, J. W., Ellis, M. & Gillot, S. R. (2016) Evaluating the performance of low cost chemical sensors for air pollution research. *Faraday discussions*, 189, 85-103.

Manikonda, A., Zíková, N., Hopke, P. K. & Ferro, A. R. (2016) Laboratory assessment of low-cost PM monitors. *Journal of Aerosol Science*, 102, 29-40.

Mead, M. I., Popoola, O. A. M., Stewart, G. B., Landshoff, P., Calleja, M., Hayes, M., Baldovi, J. J., McLeod, M. W., Hodgson, T. F., Dicks, J., Lewis, A., Cohen, J., Baron, R., Saffell, J. R. & Jones, R. L. (2013) The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks. *Atmospheric Environment*, 70, 186-203.

Moltchanov, S., Levy, I., Etzion, Y., Lerner, U., Broday, D. M. & Fishbain, B. (2015) On the feasibility of measuring urban air pollution by wireless distributed sensor networks. *Sci Total Environ*, 502, 537-47.

Northcross, A. L., Edwards, R. J., Johnson, M. A., Wang, Z. M., Zhu, K., Allen, T. & Smith, K. R. (2013) A low-cost particle counter as a realtime fine-particle mass monitor. *Environ Sci Process Impacts*, 15(2), 433-9.

Olivares, G. & Edwards, S. (2015) The Outdoor Dust Information Node (ODIN) – development and performance assessment of a low cost ambient dust sensor. *Atmospheric Measurement Techniques Discussions*, 8(7), 7511-7533.

Olivares, G., Longley, I. & Coulson, G. (2012) Development of a low-cost device for observing indoor particle levels associated with source activities in the home, *Proceedings of the International Society of Exposure Science Conference, Seattle, WA, USA*.

Piedrahita, R., Xiang, Y., Masson, N., Ortega, J., Collier, A., Jiang, Y., Li, K., Dick, R., Lv, Q. & Hannigan, M. (2014) The next generation of low-cost personal air quality sensors for quantitative exposure monitoring. *Atmospheric Measurement Techniques*, 7(10), 3325-3336.

Popoola, O. A. M., Stewart, G. B., Mead, M. I. & Jones, R. L. (2016) Development of a baseline-temperature correction methodology for electrochemical sensors and its implications for long-term stability. *Atmospheric Environment*, 147, 330-343.

Rajasegarar, S., Zhang, P., Zhou, Y., Karunasekera, S., Leckie, C. & Palaniswami, M. (2014) High resolution spatio-temporal monitoring of air pollutants using wireless sensor networks, *Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2014 IEEE Ninth International Conference on*. IEEE.

Snyder, E. G., Watkins, T. H., Solomon, P. A., Thoma, E. D., Williams, R. W., Hagler, G. S., Shelow, D., Hindin, D. A., Kilaru, V. J. & Preuss, P. W. (2013) The changing paradigm of air pollution monitoring. *Environ Sci Technol*, 47(20), 11369-77.

Sousan, S., Koehler, K., Hallett, L. & Peters, T. M. (2016a) Evaluation of the Alphasense optical particle counter (OPC-N2) and the Grimm portable aerosol spectrometer (PAS-1.108). *Aerosol Science and Technology*, 50(12), 1352-1365.

Sousan, S., Koehler, K., Thomas, G., Park, J. H., Hillman, M., Halterman, A. & Peters, T. M. (2016b) Inter-comparison of low-cost sensors for measuring the mass concentration of occupational aerosols. *Aerosol Science and Technology*, 50(5), 462-473.

Spinelle, L., Gerboles, M. & Aleixandre, M. (2015a) Performance Evaluation of Amperometric Sensors for the Monitoring of O 3 and NO 2 in Ambient Air at ppb Level. *Procedia Engineering*, 120, 480-483.

Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M. & Bonavitacola, F. (2015b) Field calibration of a cluster of low-cost available sensors for air quality monitoring. Part A: Ozone and nitrogen dioxide. *Sensors and Actuators B: Chemical*, 215, 249-257.

Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M. & Bonavitacola, F. (2017) Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2. *Sensors and Actuators B: Chemical*, 238, 706-715.

Spinellea, L., Gerbolesa, M., Aleixandreb, M. & Bonavitacolac, F. (2016) Evaluation of metal oxides sensors for the monitoring of O3 in ambient air at ppb level. *Chemical Engineering Transactions*, 54, 319-324.

Steinle, S., Reis, S., Sabel, C. E., Semple, S., Twigg, M. M., Braban, C. F., Leeson, S. R., Heal, M. R., Harrison, D., Lin, C. & Wu, H. (2015) Personal exposure monitoring of PM2.5 in indoor and outdoor microenvironments. *Sci Total Environ*, 508, 383-94.

Sun, L., Wong, K. C., Wei, P., Ye, S., Huang, H., Yang, F., Westerdahl, D., Louie, P. K., Luk, C. W. & Ning, Z. (2016) Development and Application of a Next Generation Air Sensor Network for the Hong Kong Marathon 2015 Air Quality Monitoring. *Sensors (Basel)*, 16(2), 211.

Suriano, D., Prato, M., Pfister, V., Cassano, G., Camporeale, G., Dipinto, S. & Penza, M. (2015) Stationary and Mobile Low-Cost Gas Sensor Systems for Air Quality Monitoring Applications, *Fourth Scientific Meeting EuNetAir*. Linkoping University, Linkoping, Sweden.

Thompson, J. E. (2016) Crowd-sourced air quality studies: A review of the literature & portable sensors. *Trends in Environmental Analytical Chemistry*, 11, 23-34.

Wang, Y., Li, J., Jing, H., Zhang, Q., Jiang, J. & Biswas, P. (2015) Laboratory Evaluation and Calibration of Three Low-Cost Particle Sensors for Particulate Matter Measurement. *Aerosol Science and Technology*, 49(11), 1063-1077.

White, R. M., Paprotny, I., Doering, F., Cascio, W. E., Solomon, P. A. & Gundel, L. A. (2012) Sensors and 'apps' for community-based- Atmospheric monitoring. *EM: Air and Waste Management Association's Magazine for Environmental Managers*.

WHO (2014) *Burden of disease from Ambient Air Pollution for 2012. http://www.who.int/phe/health_topics/outdoorair/databases/AAP_BoD_results_March2014.pdf (accessed 31 October 2016).*

WHO (2016) *Ambient air pollution: A global assessment of exposure and burden of disease. http://apps.who.int/iris/bitstream/10665/250141/1/9789241511353-eng.pdf?ua=1 (accessed 31 October 2016).*

Williams, R., Kaufman, A., Hanley, T., Joann, R. & Garvey, S. (2014a) *Evaluation of Field-deployed Low Cost PM Sensors. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=297517 (accessed 13 January 2017).*

Williams, R., Kilaru, V., Snyder, E., Kaufman, A., Dye, T., Rutter, A., Russell, A. & Hafner, H. (2014b) *Air Sensor Guidebook*.

Williams, R., Long, R., Beaver, M., Kaufman, A., Zeiger, F., Heimbinder, M., Hang, I., Yap, R., Acharya, B., Ginwald, B., Kupcho, K., Robinson, S., Zaouak, O., Aubert, B., Hannigan, M., Piedrahita, R., Masson, N., Moran, B., Rook, M., Heppner, P., Cogar, C., Nikzad, N. & Griswold, W. (2014c) *Sensor Evaluation Report*. *https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=277270 (accessed 31 October 2016)*.

Zakaria, N., Abdullah, J., Yusof, A., Azizan, M. & Kimpol, N. (2014) A Study of Rice Husk Total Suspended Particles (TSP) Level Using Optical Sensor in a Rice Mill Factory, 2, 29-33.

Zhou, X., Lee, S., Xu, Z. & Yoon, J. (2015) Recent Progress on the Development of Chemosensors for Gases. *Chem Rev*, 115(15), 7944-8000.

Zikova, N., Hopke, P. K. & Ferro, A. R. (2016) Evaluation of new low-cost particle monitors for PM 2.5 concentrations measurements. *Journal of Aerosol Science*, 105, 24–34.