Review of Sensors for Air Quality

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## Abstract

All references here[1](#ref-alvarado_towards_2015)–[76](#ref-zimmerman_machine_2018)

## 1. Introduction

The introduction and diffusion of the micro-sensors technology for monitoring ambient air pollution (as emerging measuring devices) is contributing to the rapid adoption of low-cost sensors (LCS) for air quality monitoring for citizen science initiative and by public authorities[36](#ref-kumar_rise_2015). Low-cost in this context is typically referring to the cost of the hardware component needed to make a measurement. LCS can provide real time measurements at lower cost allowing higher spatial coverage than the current reference methods of measurements of air pollutants. Additionally, the monitoring of air pollution with reference measurements methods requires skilled operators for the maintenance and calibration of measuring devices that are described in detailed Standard Operational Procedures[13](#ref-cen_ambient_2012_CO)–[17](#ref-cen_ambient_2014_PM). Conversely, it should be possible that LCS are operated without human intervention making it possible for unskilled users to be able to monitor air pollution without the need of important technical understanding.

However, a lot of LCS are becoming available whose performance regarding the agreement between LSC values and reference measurement can be of variable quality making it fundamental to evaluate LCS before choosing any LCS for routine measurements and case studies[40](#ref-lewis_validate_2016). As reported below, few independent tests are reported in academic publications. The rapid technological progress of LCS and the time needed to publish studies in academic journals makes publication of articles not the preferred route and the majority of the available information is found in grey literature, mainly of report types.

The major sources of information of LCS evaluation consist of AQ-SPEC[2](#ref-aq-spec_air_2015), the US-EPA and the work carried out by the Joint Research Centre[56](#ref-spinelle_evaluation_2017). (check in the article US-EPA workshop what do they say). Although a number of reviews of the suitability of sensors for ambient air quality have been published (Refs needed here), quantitative data for comparing and evaluating the agreement between sensors and reference data are mostly missing. Additionally, there is no commonly accepted protocol for the test of LCS, the metrics reported are generally diverse making it difficult to compare the performance of sensor between evaluation studies. The most common reported metrics consists of: the coefficient of determination, , the slope and intercept of regression line between sensor and reference measurements, the Root mean square of Error, RMSE and the measurement uncertainty . Here after, the results of an exhaustive review of the existing literature on LCS evaluation are presented.

The purpose of this review is to identify LCSs whose comparison with reference measurements shows the highest correlation and accuracy. For this purpose, we performed a comprehensive review about the performance of commercial LCSs. We have aggregated summary statistics about the agreement between sensors and reference instruments. Although in Europe, the main metrics to evaluate the performance of measuring methods consists of the measurement uncertainty, this metrics could not be used in our study since the majority of studies do not report it (*174* records out of *1304* total number of records reporting RMSE and other metrics for uncertainty ) give the number of studies with this parameter?). Conversely, we had to rely on most common metrics, i. e., the coefficient of determination , the slope and intercept of linear regression line between sensor and reference measurement and, in few cases, the Root Mean Square of Error that were scrutinized and analyzed to identify sensors that could potentially be complementary to the reference methods of air quality monitoring.

The market of LCSs for ambient air monitoring only consists of a small number of sensor model types that are manufactured by a few companies. These LCSs, are usually known as Original Equipment Manufacturers (OEM).

As per definition, an **OEM** is a chemical cell or physical unit that produces an analytically useful signal by detecting or measuring the analyte. On the other hand a **Sensor System (SS)** or **sensor note** is an integrated set of hardware that uses one or more sensors to detect and/or measure a chemical concentration or quantity that is able to supply real time measurements. A sensor systems contain a number of common components in addition to the basic sensing/analytical element that is used for detection. Common core components and functions may include:

* Sensing element or detector (actually the sensor)
* Sampling capability (active or passive sampling)
* Power systems, including batteries
* Analogue to digital conversation
* Signal processing
* Local data storage
* Data transmission
* Housing / casing

OEMs use chemical and physical techniques phenomena to sense pollutant in ambient air. However, in order to simplify measurement operations, calibration and data transfer into a convenient sensor object, OEMs need be integrated into a sensor system (SS), consisting of electronic boards, software and protective box gathering the hardware, software and OEM sensors.

The use of low-cost sensors is extensively interesting for citizen-science initiatives. Therefore, Small Medium Enterprises were able to sell sensor-systems which could be deployed by citizen who wanted to monitor air quality in a chosen environment. Up to date, there are several sensor systems using sensors from the same OEM. However, outputs from these sensors system often differ from each other. The ideal candidate sensor system would show good agreement with reference measurements and, at the same time, provide sensor raw data allowing to be calibrated using open source correction algorithms. The number of air pollutants being measured was also a parameter taken into consideration. Finally, the price of a low cost-sensor was also taken into account.

## 2. Methods

### 2.1. Data sources

About *1304* records have been systematically gathered from the Scopus database and the World Wide Web collected into a Zotero database (<https://www.zotero.org/>) that JRC established, the AirMontech web site (<http://db-airmontech.jrc.ec.europa.eu/search.aspx>) that JRC keeps on maintaining that were supplied with scopus, researchGate and Google search for peer-reviewed studies of sensors for air quality and air pollution. The research was focused on sensors for Particulate Matter , Ozone , Nitric Dioxide and Carbon Monoxide . A few references are also included for nitrogen monoxide sensors . We have started evaluating summary statistics from the correlation of sensors and reference measurements (validation).

The research covered the period between 2010 and 2018 (year of publication). Data gathered from sensor studies were reviewed according to criteria described in the following sections. Reviewed sensor data were used to populate a database that was used to generate summary statistics about characteristics and performances of sensors. Overall, about a number of *62* independent studies were found from different sources from reports, peer-review papers and sensors manufacturers

### 2.2. Data collection

Most of the reviewed studies reported regression parameters obtained from the comparison between sensors and reference measurements. Records from regression parameters were the result of both calibration and comparison of the sensor with a reference instrument. In the case of calibration, we identified four types of most used regression models: linear, multilinear (MLR), quadratic and logarithmic. Finally, only records from *“living”* and *“updated”* sensors were retained to compare performances from different sensor systems.

### 2.3. Evaluation criteria

We have carried out an extensive literature review of OEM sensors and sensor systems (SS) that were used to estimate concentration of air pollutants against a reference systems during field and laboratory tests. The purpose was to gather quantitative information about the performance of sensors according to the following criteria:

1. Agreement between sensor and reference measurements
2. Availability of raw data, transparency of data treatment and possibility of a-posteriori calibration
3. Capability to measure multiple pollutants
4. Affordability of sensor systems taking into consideration the number of provided sensors
5. Capacity to satisfy the requirement of interoperability of data according to the INSPIRE directive
6. Automatic data-transfer and website visualization of sensor data

The review was focused on available commercial OEMs and sensor systems measuring concentrations of Particulate Matter (, , ), Nitric Dioxide () Carbon Monoxide (), and . **Table 1** reports the number of records, by pollutant and operating technology, gathered in literature about validation and testing of OEMs / sensor systems against a reference system. Records were collected from laboratory (*141*) and field tests (*1160*).

**Table 1.** Number of analyzed records for OEMs/Sensor Systems by pollutant and by type of technology.

|  |  |  |  |
| --- | --- | --- | --- |
| pollutant | type | n. records | references |
|  | electrochemical | 69 |  |
|  | MOs | 23 |  |
|  | electrochemical | 49 |  |
|  | electrochemical | 139 |  |
|  | MOs | 37 |  |
|  | electrochemical | 69 |  |
|  | MOs | 53 |  |
|  | UV | 10 |  |
|  | Electrical | 6 |  |
|  | nephelometer | 216 |  |
|  | OPC | 347 |  |
|  | Electrical | 6 |  |
|  | OPC | 92 |  |
|  | nephelometer | 32 |  |
|  | OPC | 156 |  |

## 3. Classification of sensors

For each model of sensor system we ~~could determine~~ identified which the manufacturer of OEM sensor and the manufacturer of Sensor system itself including the sensor box, acquisition system, electronic board and internal software for data transfer and data analysis.

Each database record describing the laboratory or field performance of sensors was considered valuable only if it reported information about laboratory test and/or comparison against a reference measurement. We want to stress out that the same OEMs can be used in Sensor Systems from different manufacturers. Overall, we found *72* manufacturers of OEM *(379)*, or sensor systems *(925)* in total. In addition, we identified *25* projects about the deployment of the OEMs/sensor systems under different operational conditions. Out of *1304* records collected from literature, we identified *1304* records from “active” sensors and sensor systems (non-discontinued manufacturing).

Commercial LCSs may have costs of ranging from few euros to thousands of dollars for more complex and multi-pollutant and fully autonomous etection devices including hardware costs. Commonly speaking, “low-cost” refers to the cost of a sensor system compared against the cost of a reference instrument measuring the air pollutant[39](#ref-lewis_low-cost_2018). More recently, ultra-affordable OEMs are starting to appear on the market. Many of them are designed to be integrated in the Internet of things (IoT) network of devices. Currently, for the detection of particulate matter, it is possible to purchase optical sensor at prices of few hundreds euros to few tens of euros from devices manufactured in emerging economies such as the Republic of China and Republic of Korea[65](#ref-the_world_air_quality_index_sensing_2019) Most of these senosrs are starting to achieve performances comparable to professional monitors and aloso to low-cost OEMs manufactured in the Western world.

### 3.1. Methodology for data acquisition

We identified two methodologies to test sensors against a reference systems:

1. Use of sensor devices connected to a custom-made data acquisition system to acquire raw data from the sensor to estimate pollutant concentrations. A calibration curve could be applied to the raw data to validate the sensor against a reference system. In most cases, the sensor devices were OEMs integrated in an electronic board. Data acquisition and data processing could be operated by an **“open source”** software tuned according to different calibration parameters and environmental conditions. Overall, we identified *899* records among OEMs and sensor systems using an open source software for data management. We could find several manufactures using the same OEM but with different data acquisition systems as well as calibration algorithms. Usually, outputs from these sensor were already in the same measurement units of the reference system.
2. Use of sensor systems with built-in OEM sensors, electronic board and calibration algorithms but without the possibility to change any parameters of the sensor set by the manufacturer. In most cases, the sensor system was previously calibrated against a reference system or, the calibration parameters were remotely adjusted by the manufacturer. These sensors systems have been identified as **“black box”** because of the impossibility to be tuned by the user. Overall, we identified *402* records among OEMs and sensor systems NOT using an open source software for data management.

Clear definiton about the current techniques used by different type of sensor (electrochemical, metal oxides, optical particulate counter, optical sensors) is reported in a recent work by WMO[39](#ref-lewis_low-cost_2018). This work also reports the several limitation of each type of sensor sucgh as, interference with other gaseous pollutant, drifts, correction to applyed and aging effect.

### 3.2. Sensors for air quality

For the detection of Particulate Matter, the largest number of calibration/validation tests was found for Optical Particle Counters (OPC) with *595* records followed by Nephelometers with *248* records (**Table 2**). Both systems detect particulate matter by measuring the light scattered by particles, with the OPC being able to directly count particles according to their size. On the other hand, nephelometers estimate particle density that is subsequently converted into particle mass. For the detection of gaseous pollutant such as , and , the largest number of tests was found for electrochemical sensors with *326* records, followed by metal oxides sensors (MOs) with *113* records. Electrochemical sensors are based on a chemical reactions between gases in the air and the electrode in a liquid inside the sensor. On the Other hand, in a metal oxide sensor (resistive sensor, semiconductor) gases in the air react on the surface of the sensor modifying its resistance.

**Table 2** reports the models of OEM sensors currently used to measure concentration of particulate matter according their their technology type and the cut-off of particulate size. For the sake of clarity, we aggregated records from together with , and . The same was done for records that were aggregated with coarse . Models of sensor systems measuring particulate matter concentration were also reported in **Table 3**[1](#ref-alvarado_towards_2015)–[4](#ref-badura_optical_2018),[8](#ref-borghi_precision_2018)–[10](#ref-budde_suitability_2018),[12](#ref-cavaliere_development_2018),[18](#ref-chakrabarti_performance_2004),[20](#ref-crilley_evaluation_2018),[22](#ref-dacunto_determining_2015),[24](#ref-feinberg_long-term_2018),[25](#ref-gao_distributed_2015),[27](#ref-gerboles_calibration_2018)–[34](#ref-kelly_ambient_2017),[37](#ref-kunak_wireless_2017),[38](#ref-laquai_particle_2017),[42](#ref-manikonda_laboratory_2016),[47](#ref-mukherjee_assessing_2017)–[49](#ref-olivares_outdoor_2015),[51](#ref-pillarisetti_small_2017),[53](#ref-sousan_evaluation_2016),[62](#ref-steinle_personal_2015),[68](#ref-viana_field_2015),[69](#ref-wang_laboratory_2015),[72](#ref-williams_evaluation_2014)–[75](#ref-zikova_estimating_2017). Very often, sensor systems might use the same OEM to integrate it inside an electronic board to control the data acquisition/data treatment through a customized software. In very few cases, the same model of sensor system was tested using different types of OEM sensors when performing validation tests.

**Table 3.** Model of OEMs for the detection of Particulate Matter.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| model | type | pollutant |  |  | references |
| **AirBeam** | OPC |  |  |  |  |
| **CairClip PM2.5** | nephelometer |  |  |  |  |
| **DataRAM pDR-1200** | nephelometer |  |  |  |  |
| **DN7C3CA006** | nephelometer |  |  |  |  |
| **DSM501A** | nephelometer |  |  |  |  |
| **Dylos DC1100** | OPC |  |  |  |  |
| **Dylos DC1100 PRO** | OPC |  |  |  |  |
| **Dylos DC1700** | OPC |  |  |  |  |
| **GP2Y1010AU0F** | nephelometer |  |  |  |  |
| **OPC-N2** | OPC |  |  |  |  |
| **OPC-N3** | OPC |  |  |  |  |
| **PMS-SYS-1** | nephelometer |  |  |  |  |
| **PMS3003** | OPC |  |  |  |  |
| **PMS5003** | OPC |  |  |  |  |
| **PMS7003** | OPC |  |  |  |  |
| **PPD42NS** | nephelometer |  |  |  |  |
| **SDS011** | OPC |  |  |  |  |
| **SidePak AM510** | nephelometer |  |  |  |  |
| **Speck** | nephelometer |  |  |  |  |
| **ZH03A** | nephelometer |  |  |  |  |
| **Dylos DC1100 PRO** | OPC |  |  |  |  |
| **Dylos DC1700** | OPC |  |  |  |  |
| **GP2Y1010AU0F** | nephelometer |  |  |  |  |
| **OPC-N2** | OPC |  |  |  |  |
| **SDS011** | OPC |  |  |  |  |
| **OPC-N2** | OPC |  |  |  |  |

**Table 3.** Models of Sensor Systems for the detection of Particulate Matter.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| model | type | pollutant |  |  | references |
| **Air Quality Station** | OPC |  |  |  |  |
| **AirAssure** | nephelometer |  |  |  |  |
| **AirBeam** | nephelometer |  |  |  |  |
| **AirBeam** | OPC |  |  |  |  |
| **AirNut** | nephelometer |  |  |  |  |
| **AIRQino** | OPC |  |  |  |  |
| **AirThinx** | OPC |  |  |  |  |
| **AirVisual Pro** | nephelometer |  |  |  |  |
| **AQY v0.5** | OPC |  |  |  |  |
| **Cair** | OPC |  |  |  |  |
| **CAIRSENSE-1** | nephelometer |  |  |  |  |
| **CAIRSENSE-1** | OPC |  |  |  |  |
| **CAIRSENSE-2** | nephelometer |  |  |  |  |
| **CAIRSENSE-2** | OPC |  |  |  |  |
| **CAIRSENSE-3** | nephelometer |  |  |  |  |
| **CAIRSENSE-3** | OPC |  |  |  |  |
| **CAM\_10** | OPC |  |  |  |  |
| **Clarity Node** | nephelometer |  |  |  |  |
| **DC1100 PRO** | OPC |  |  |  |  |
| **DSM501A** | nephelometer |  |  |  |  |
| **Dylos DC1100** | OPC |  |  |  |  |
| **E-Sampler** | OPC |  |  |  |  |
| **ECN\_Box\_10** | nephelometer |  |  |  |  |
| **ECN\_Box\_38** | nephelometer |  |  |  |  |
| **Egg (2018)** | OPC |  |  |  |  |
| **Egg v.2 (PM)** | nephelometer |  |  |  |  |
| **EMMA** | OPC |  |  |  |  |
| **Foobot** | OPC |  |  |  |  |
| **Hanvon N1** | nephelometer |  |  |  |  |
| **KUNAKAIR P10 V2** | OPC |  |  |  |  |
| **Laser Egg** | nephelometer |  |  |  |  |
| **Met One-ES642** | nephelometer |  |  |  |  |
| **Met One (NM)** | OPC |  |  |  |  |
| **MicroPEM** | nephelometer |  |  |  |  |
| **PA-I** | OPC |  |  |  |  |
| **PA-I-Indoor** | OPC |  |  |  |  |
| **PA-II** | OPC |  |  |  |  |
| **Partector** | Electrical |  |  |  |  |
| **PATS+** | nephelometer |  |  |  |  |
| **PMS-SYS-1** | nephelometer |  |  |  |  |
| **PMS1003** | OPC |  |  |  |  |
| **PMS3003** | OPC |  |  |  |  |
| **Portable** | OPC |  |  |  |  |
| **Pure Morning P3** | OPC |  |  |  |  |
| **Speck** | nephelometer |  |  |  |  |
| **UBAS** | nephelometer |  |  |  |  |
| **uHoo** | nephelometer |  |  |  |  |
| **AirSensorBox** | OPC |  |  |  |  |
| **CAM\_10** | nephelometer |  |  |  |  |
| **CAM\_11** | OPC |  |  |  |  |
| **ELM** | nephelometer |  |  |  |  |
| **Met One - 831** | OPC |  |  |  |  |
| **Eco PM** | OPC |  |  |  |  |

**Table 4** and **Table 5** reports the models of OEM and sensor systems, respectively, currently used to measure concentration of gaseous air pollutants , , and, according their their type of technology.[2](#ref-aq-spec_air_2015),[6](#ref-bettair_bettair_2017),[7](#ref-bigi_performance_2018),[9](#ref-borrego_assessment_2016),[11](#ref-castell_can_2017),[12](#ref-cavaliere_development_2018),[19](#ref-cordero_using_2018),[21](#ref-cross_use_2017),[23](#ref-duvall_performance_2016),[24](#ref-feinberg_long-term_2018),[26](#ref-gerboles_airsenseur_2015),[28](#ref-gillooly_development_2019),[31](#ref-jiao_community_2016),[37](#ref-kunak_wireless_2017),[43](#ref-marjovi_extending_2017)–[46](#ref-mueller_design_2017),[50](#ref-piedrahita_next_2014),[55](#ref-spinelle_evaluation_2016),[57](#ref-spinelle_field_2015),[58](#ref-spinelle_field_nodate),[60](#ref-spinelle_report_2013),[61](#ref-spinelle_report_2013-1),[63](#ref-sun_development_2016),[64](#ref-sun_development_2017),[66](#ref-united_states_environmental_protection_agency_evaluation_2015),[67](#ref-vaughn_characterization_2010),[71](#ref-wei_impact_2018),[73](#ref-williams_sensor_2014),[76](#ref-zimmerman_machine_2018)

**Table 4** . Model of OEMs for the detection of , , and .

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| model | type | pollutant |  |  |  | references |
| **CairClip NO2-F** | electrochemical |  |  |  |  |  |
| **CairClip O3/NO2** | electrochemical |  |  |  |  |  |
| **Cariclip NO2-F** | electrochemical |  |  |  |  |  |
| **EMMA** | electrochemical |  |  |  |  |  |
| **MiCS-2710** | MOs |  |  |  |  |  |
| **MICS-4514** | MOs |  |  |  |  |  |
| **NO2-A1** | electrochemical |  |  |  |  |  |
| **NO2-B4** | electrochemical |  |  |  |  |  |
| **NO2-B42F** | electrochemical |  |  |  |  |  |
| **NO2-B43F** | electrochemical |  |  |  |  |  |
| **NO2 3E50** | electrochemical |  |  |  |  |  |
| **Platypus NO2** | MOs |  |  |  |  |  |
| **S-500** | electrochemical |  |  |  |  |  |
| **S-500** | MOs |  |  |  |  |  |
| **CO-B4** | electrochemical |  |  |  |  |  |
| **CO 3E300** | electrochemical |  |  |  |  |  |
| **MICS-4514** | MOs |  |  |  |  |  |
| **TGS-5042** | electrochemical |  |  |  |  |  |
| **NO-3E100** | electrochemical |  |  |  |  |  |
| **NO-B4** | electrochemical |  |  |  |  |  |
| **CairClip O3/NO2** | electrochemical |  |  |  |  |  |
| **FIS SP-61** | MOs |  |  |  |  |  |
| **O3-3E1F** | electrochemical |  |  |  |  |  |
| **O3-B4** | electrochemical |  |  |  |  |  |
| **S-500** | MOs |  |  |  |  |  |
| **SM50** | electrochemical |  |  |  |  |  |

**Table 5** . Model of Sensor Systems for the detection of , , and .

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| model | type | pollutant | pollutant.y |  |  | references |
| **AGT ATS-35 NO2** | MOs |  |  |  |  |  |
| **AirCasting** | MOs |  |  |  |  |  |
| **AirCube** | electrochemical |  |  |  |  |  |
| **AIRQino** | MOs |  |  |  |  |  |
| **AirSensEUR (v.2)** | electrochemical |  |  |  |  |  |
| **AirVeraCity** | electrochemical |  |  |  |  |  |
| **AQM 60** | electrochemical |  |  |  |  |  |
| **AQM 60** | MOs |  |  |  |  |  |
| **AQMesh v.4.0** | electrochemical |  |  |  |  |  |
| **AQY v0.5** | electrochemical |  |  |  |  |  |
| **ARISense** | electrochemical |  |  |  |  |  |
| **Bettair** | electrochemical |  |  |  |  |  |
| **CAIRSENSE-1** | electrochemical |  |  |  |  |  |
| **CAM\_11** | electrochemical |  |  |  |  |  |
| **ECN\_Box\_10** | electrochemical |  |  |  |  |  |
| **Egg v.1** | MOs |  |  |  |  |  |
| **Egg v.2** | electrochemical |  |  |  |  |  |
| **ELM** | MOs |  |  |  |  |  |
| **ENEA/AirSensorBox** | electrochemical |  |  |  |  |  |
| **Intel Berkeley Badge** | electrochemical |  |  |  |  |  |
| **Intel Berkeley Badge** | MOs |  |  |  |  |  |
| **ISAG** | MOs |  |  |  |  |  |
| **KUNAKAIR A10 V2** | electrochemical |  |  |  |  |  |
| **M-POD** | MOs |  |  |  |  |  |
| **MAS** | electrochemical |  |  |  |  |  |
| **NanoEnvi** | electrochemical |  |  |  |  |  |
| **RAMP** | electrochemical |  |  |  |  |  |
| **SENS-IT** | MOs |  |  |  |  |  |
| **SNAQ** | electrochemical |  |  |  |  |  |
| **Spec** | electrochemical |  |  |  |  |  |
| **Urban AirQ** | electrochemical |  |  |  |  |  |
| **Vaisala AQT410 v.1.11** | electrochemical |  |  |  |  |  |
| **Vaisala AQT410 v.1.15** | electrochemical |  |  |  |  |  |
| **AIRQino** | electrochemical |  |  |  |  |  |
| **AQMesh v.4.0** | electrochemical |  |  |  |  |  |
| **CAIRSENSE-2** | electrochemical |  |  |  |  |  |
| **Smart Citizen Kit** | MOs |  |  |  |  |  |
| **AirCube** | electrochemical |  |  |  |  |  |
| **2B Tech. (POM)** | UV |  |  |  |  |  |
| **AirCube** | electrochemical |  |  |  |  |  |
| **AQMesh v.4.0** | electrochemical |  |  |  |  |  |
| **AQT410 v.1.11** | electrochemical |  |  |  |  |  |
| **AQT410 v.1.15** | electrochemical |  |  |  |  |  |
| **AQY v0.5** | MOs |  |  |  |  |  |
| **CAIRSENSE-1** | MOs |  |  |  |  |  |
| **CAIRSENSE-2** | MOs |  |  |  |  |  |
| **CAIRSENSE-4** | electrochemical |  |  |  |  |  |
| **CAIRSENSE-4** | MOs |  |  |  |  |  |
| **ELM** | MOs |  |  |  |  |  |
| **MAS** | UV |  |  |  |  |  |
| **NanoEnvi** | MOs |  |  |  |  |  |
| **uHoo** | MOs |  |  |  |  |  |

## 4. Calibration of Sensors

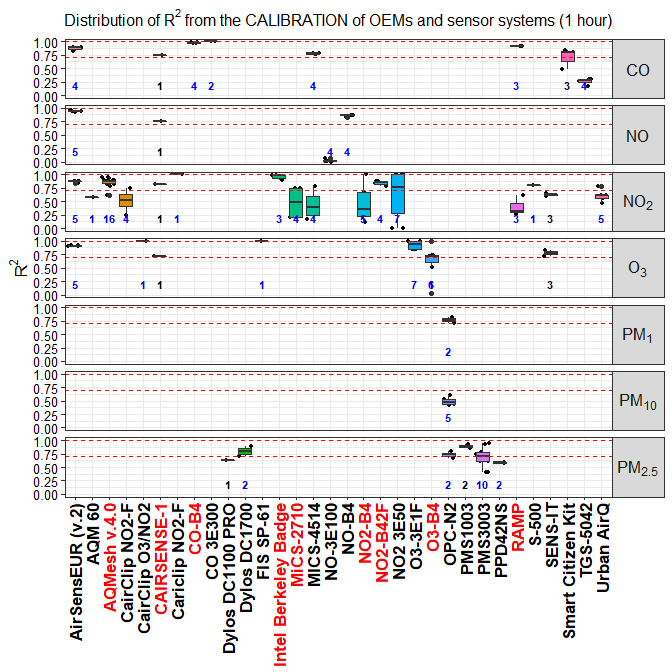
Calibration of the sensor is considered an information somewhat a sensitive information from most of the sensor manufacturers. Several studies performed calibration of sensors during laboratory or field tests. The calibration consisted in the application of a regression model in order to adjust the response of the sensor to a reference system. We found calibration records for both OEMs and sensor systems. Overall, we gathered over *318* records of calibrated sensors using different types of mathematical models **(Table 6)** and at different time resolutions. The linear model and the multi linear regression model (MLR) were most used to calibrate the sensor response against a reference measurement. Other calibration methodologies used exponential, logarithmic, quadratic, and few types of neural networks models. In the case multi linear regression, covariates such as meteorological parameters *Temperature* and *Relative Humidity*, and gaseous pollutant such as Nitric Dioxide (), Nitric Monoxide () and Ozone (), were used to optimize the calibration. Some types of model also include the as covariate. The calibration of OEMs was performed using raw data of the sensor. On the other hand, for sensor systems, the calibration was carried out using the units of the reference system.

**Table 6.** Types of calibration models used for the calibration of sensors at different time resolutions

|  |  |  |
| --- | --- | --- |
| calibration model | n. records | references |
| **ANN** | 8 |  |
| **exp** | 9 |  |
| **linear** | 96 |  |
| **log** | 20 |  |
| **MLR** | 122 |  |
| **quad** | 45 |  |
| **RF** | 10 |  |
| **SVM** | 4 |  |
| **SVR** | 4 |  |

As explained above, from the analyzed records, we found several type of regression model that were used to calibrate sensors from OEM and sensor systems (**Table 6**) against reference systems. In order the estimate quality of the used calibration model, we reported the coefficient of determination as indication of the amount of total variability explained by the model. is usually defined as:

where is the sum of squares of residuals and is the total sum of squares. On a first instance, The coefficient of determination can be used as indication of performance of the calibration model chosen to validate the sensor with a reference system. In addition to simple linear models, raw sensor data were validated using multilinear and quadratic models models (**Table 5**) which included the use of covariates to improve the quality of the calibration.

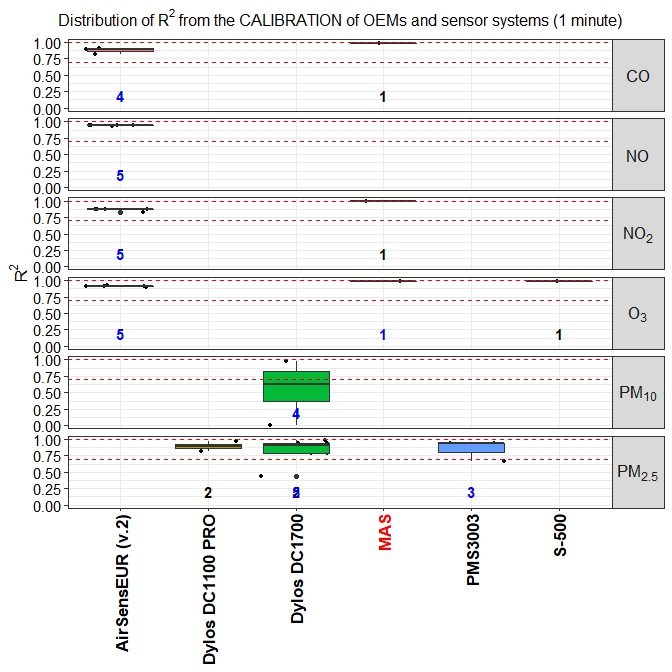


**Figure 1.** Distribution of for OEMs and sensor systems against the reference for different pollutants. Records were averaged over a time-scale of 1 hour. Dashed lines indicate the value of 0.7 and 1.0. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

Calibration of sensor data against a reference system was found to be carried out using input data at different time resolution. Therefore, in order to make a comparison of obtained at the same time resolution data, we chose records averaged over different time-scale of 1 hour **(Figure 1)** and 1 minute **(Figure 2)**. Most of these records were from OEMs *(109)* whereas only a limited number were from sensor systems *(109)*.

**Figure 1** and **Figure 2** report the distribution of found from the calibration of OEMs and sensor systems measuring , , , , and against reference systems at a time-resolution of 1 hour and 1 minute, respectively. Records from the calibration of sensors measuring , and were grouped together with records from the calibration of sensors measuring . We want to point out that calibration of OEMs and sensor systems, were mostly performed using multi-linear regression models and linear models (Table 7).

As shown in Figure 1 and Figure 2, for values of ~ 1 were found for the sensors **PMS1003** by **Plantower**[34](#ref-kelly_ambient_2017) at 1-hour resolution and for the the **PMS3003** , **Dylos DC1100 PRO** and **DC1700** by **Dylos** at a resolution of 1 minute.[2](#ref-aq-spec_air_2015),[62](#ref-steinle_personal_2015),[74](#ref-zheng_field_2018) The Plantower and Dylos sensors showed higher when calibrated with 1 minute resolution reference data. Other sensors such as, the **OPC-N2** by **AlphaSense**[2](#ref-aq-spec_air_2015) reported values of falling within the range of 0.7 - 1.0 at a resolution of 1 hour. The same OEM sensor OPC-N2, reported values of just above 0.7 when measuing while it did not show a good performance when measuring [2](#ref-aq-spec_air_2015). We need to stress out that optical sensors, such as OPCs and nephelometers, are somewhat limited when detecting coarse particulate patter because of the low-efficiency of the sampling system when sampling large particles in ambient air.



**Figure 2.** Distribution of for OEMs and sensor systems against the reference for different pollutants. Records were averaged over a time-scale of 1 minute. Dashed lines indicate the value of 0.7 and 1.0. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

Most of regression models used for the calibration of sensors detecting gaseous pollutants used a time-resolution of 1 hour. For the calibration of sensors measuring , the largest values of was reported for the OEM sensors **FIS SP-61** by **FIS** and **O3-3E1F** by **CityTechnology**, when using a time-resolution of 1 hour (**Figure 1**)[55](#ref-spinelle_evaluation_2016). On the other hand, when using a time-resolution of 1 minute, values of ~ 1 were found for the sensor system **AirSensEUR (v.2)** by **LiberaIntentio**[27](#ref-gerboles_calibration_2018) as well as for the OEM **S-500** by **Aeroqual**[2](#ref-aq-spec_air_2015) (**Figure 2**). The AirSensEUR uses a built-in OEM **OX-A431**. We want to point out that, most of the MLR models used for calibration ozone sensors foresees the use of reference because of the strong oxidizing effect of on gas sensors with consequent formation of .

For the calibration of sensors measuring we found values of within the range 0.7 - 1.0 for the OEM sensor **NO2-B42F** (by Alphasense[71](#ref-wei_impact_2018)), at a time resolution of 1 hour, and the sensor systems **AirSensEUR (v.2)** (by LiberaIntentio)[27](#ref-gerboles_calibration_2018)) and **MAS**[63](#ref-sun_development_2016) at a time resolution of 1 minute (Figure 2). We need to point out that for the measurement of , the AirSensEUR (v.2) uses the OEM sensor NO2-B43F by AlphaSense.

Most of the records about the calibration of sensor measuring showed high values of . As shown in Figure 1, the OEMs **CO 3E300** by **City Technology**[26](#ref-gerboles_airsenseur_2015) and **CO-B4** by **Alphasense**[71](#ref-wei_impact_2018) reported ~ 1 for time-resolution of 1 hour. High values of were also reported for the sensor system **AirSensEUR (v.2)** when calibrating for at a time-resolution of 1 minute (Figure 2)[27](#ref-gerboles_calibration_2018). Other sensors reporting values of within the range 0.7 - 1.0 where the **MICS-4515** by and **SGX Sensortech**[50](#ref-piedrahita_next_2014), the **Smart Citizen Kit** by **Acrobotic**[2](#ref-aq-spec_air_2015) and the **RAMP**[76](#ref-zimmerman_machine_2018). All these sensors used 1 hour time-resolution data.

## 5. Comparison with reference systems

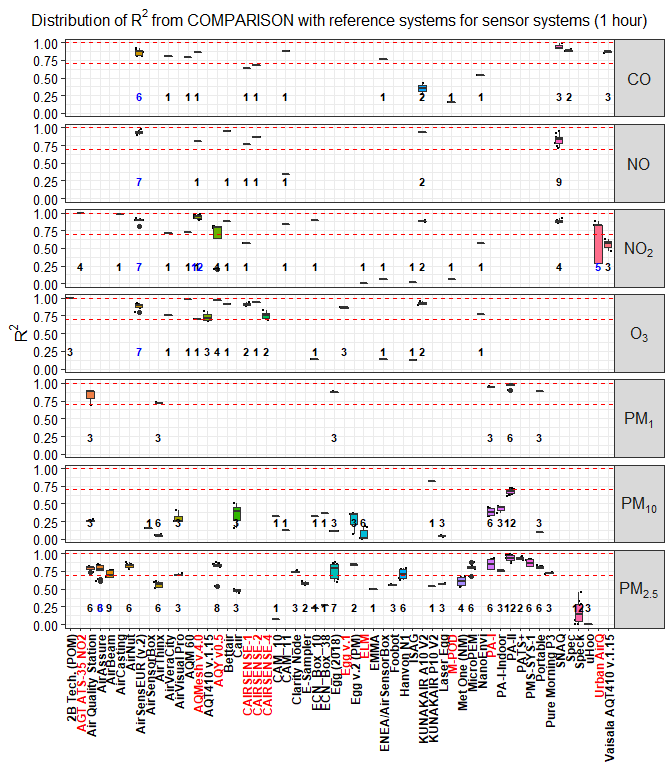
We found about *1111* records about the comparison of calibrated sensors against a reference instrument. All comparisons were carried out by using a *linear regression* model between calibrated and reference data. The performance of the regression was evaluated with the coefficient of determination and the *slope* of the regression. About the uncertainty resulting from the comparison, we must to point out that not all the analyzed records reported the *Root Mean Square Error (RMSE)* of the regression therefore, we decided to omit it in the present review.

The coefficient of determiantion is usually used as indication of “usefulness” or “godness” of fit obained from regression models comparing sensor measurements with reference measurements. However, is a partial measures of how sensors data are close to reference data according to a regression model[5](#ref-barrett_coefficient_1974). A larger reflects an increase in the predictive precision of the regression model but it ignores the loss in information due to possible loss in degrees of freedom. A significance test is therefore suggested in this case. Alternatively, can be viewd as a measure of both goddness of fit (in the sense of how close to reference data) and the slope of the regression. However, if the goodness of fit about the regression is fixed, then the slope will increase and consequentely also the . Therefore, when it happens to calibrate different datasets, calibration using slope and values close to 1.0 might be less precise than calibration using smaller values of slope and .

In this work, records gathered from the comparison of sensors with reference systems came from OEMs and sensor systems using a custom calibration or a built-in calibration directly setup by the manufacturer.

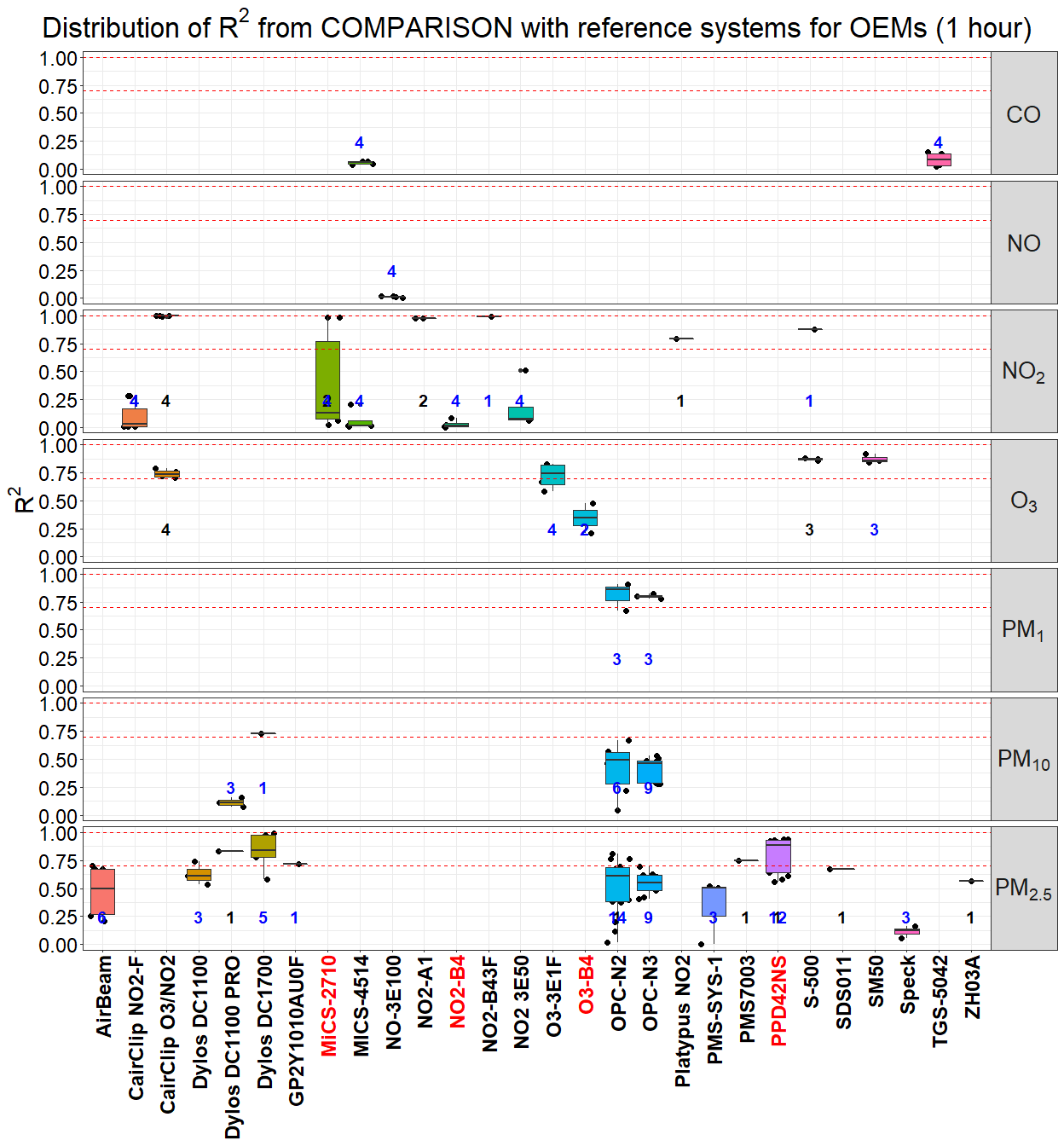
As for the records collected from the calibration of sensor, comparison with reference system was carried out at different time-resolutions. Here we only report comparisons performed at a time-resolution of 1 hour with *418* and *175* records from sensor systems and OEMs, respectively.

Figure 3 shows the distribution of for sensors systems measuring , , , , and against reference at 1-hour time-resolution. For the measurements of particulate matter, most of the comparisons were performed during field tests with the highest obtained from the sensor **PA-II** by **PurpleAir**[2](#ref-aq-spec_air_2015) and **PATS+** by **Belkley Air**[51](#ref-pillarisetti_small_2017). This sensors reported values of between 0.8 and 1.0. Other sensors with values falling in the range 0.7-1.0 were identified in the **PMS-SYS-1** by **Shinyei**, the **Dylos 1100 PRO** by **Dylos**, the **MicroPEM** by **RTI**, the **AirNUT** by **Moji China**  the **Egg (2018)** by **Air Quality Egg** and the **Air Quality Station** by **AS LUNG**[2](#ref-aq-spec_air_2015). Records from other sensors showed different values of depending of the type of field test and for the averaging time chosen to process the time-series of data. We need to point out that the performance of sensor systems measuring , on average, was very poor.

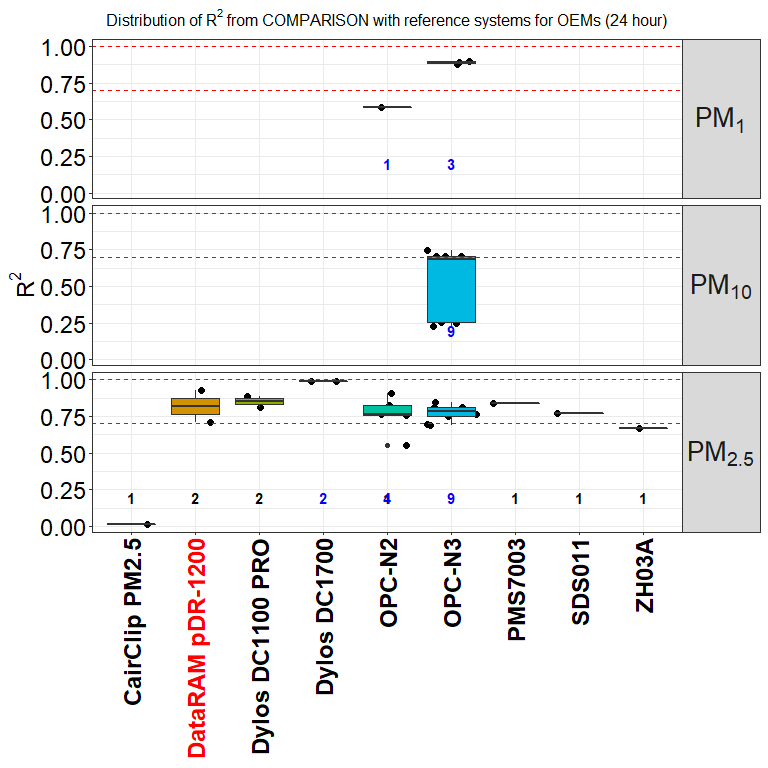


**Figure 3.** Distribution of from the comparison of all sensor systems against reference systems. Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

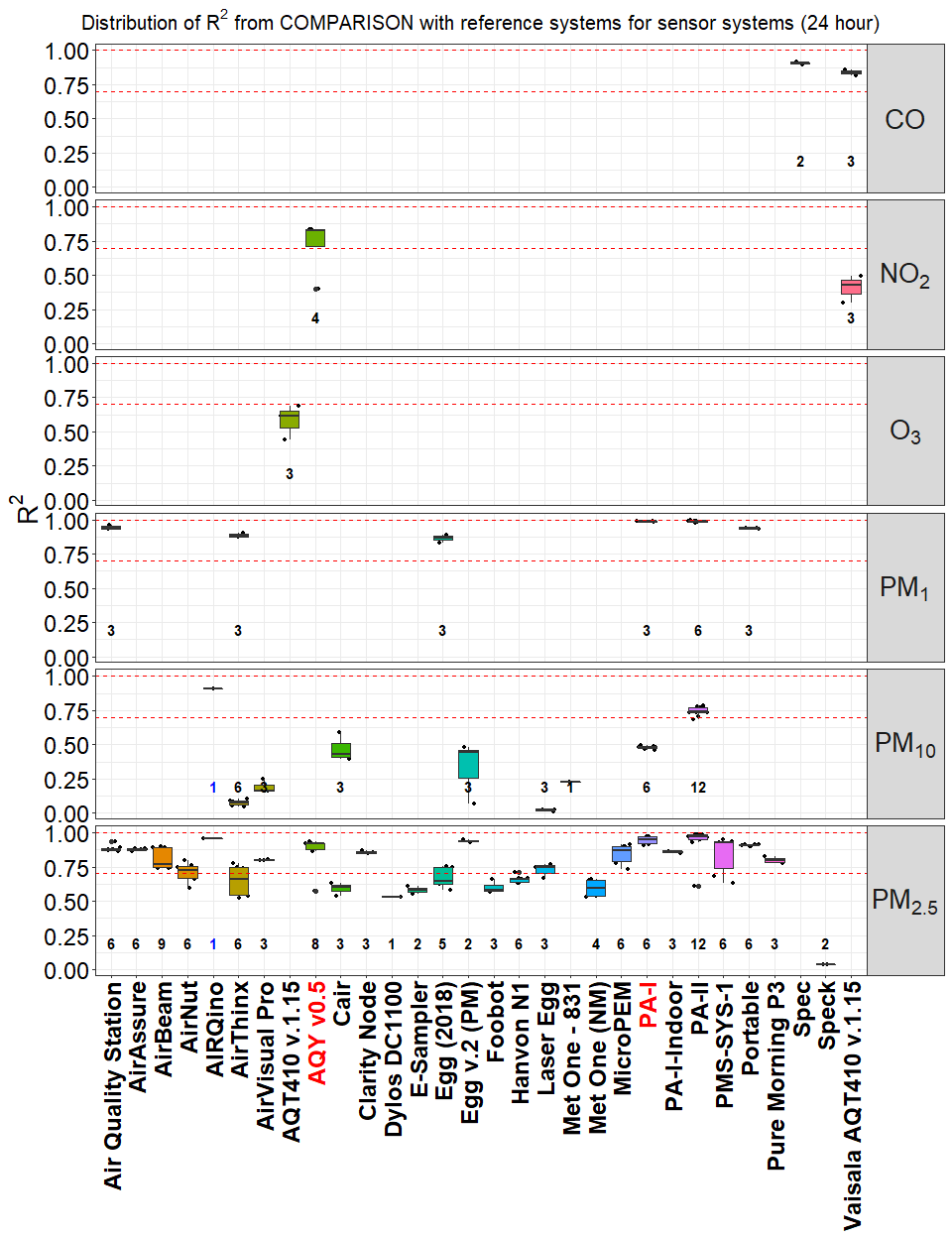
For gaseous pollutants, high values were found for the sensor systems **2B Tech. (POM)** by **2B Technologies** ()[2](#ref-aq-spec_air_2015), the **AirSensEUR (v.2)** by **LiberaIntentio**[27](#ref-gerboles_calibration_2018) the **Bettair** by **Bettair Cities**[6](#ref-bettair_bettair_2017) the **AirCasting** by **HabitatMap**[72](#ref-williams_evaluation_2014) the **KUNAKAIR A10 V2** by **kunak**[37](#ref-kunak_wireless_2017) (, , and ), the **Spec**, the **AQMesh** (**Figure 3**). This sensors reported values of between 0.8 and 1.0. As shown in Figure 3, we found a non-negligible number of records for sensor systems whose resulting from the comparison with reference systems was within the range 0.7 - 1.0 using 1-hour averaged data. We want to point out that, among all tested sensor systems, only the **AirSensEUR (v.2)** was the only one measuring multiple pollutants.



**Figure 4.** Distribution of from the comparison of all OEMs against reference systems.Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.



**Figure 5.** Distribution of from the comparison of all OEMs against reference systems.Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.



**Figure 6.** Distribution of from the comparison of all sensor systems against reference systems.Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

The comparison of OEMs against reference systems, showed only few sensors for the measurement of had within the range 0.7 - 1.0 when average over a time-scale of 1 hour. Among them we could identify the **Dylos DC 1700**[30](#ref-holstius_field_2014),[42](#ref-manikonda_laboratory_2016),[53](#ref-sousan_evaluation_2016),[77](#ref-jovasevic-stojanovic_use_2015) and the **OPC-N2** (**Figure 4**)[2](#ref-aq-spec_air_2015),[4](#ref-badura_optical_2018),[20](#ref-crilley_evaluation_2018),[24](#ref-feinberg_long-term_2018),[47](#ref-mukherjee_assessing_2017) when measuring . On the other hand, when the comparison was performed over a time-scale of 24 hour we found within the range 0.7 - 1.0 for several OEMs which included the **PMS7003** by **Plantower**[4](#ref-badura_optical_2018), the **SDS011** by **Nova Fitness**[4](#ref-badura_optical_2018), the **OPC-NO2**[2](#ref-aq-spec_air_2015), and the **Egg v.2 (PM)** by **Air Quality Egg**[2](#ref-aq-spec_air_2015) when measuring (**Figure 5**). The same behaviour was observed from the comparison of sensor systems against a reference system when measuring 24-hour averaged data of . As we can see from **Figure 6**, several sensor systems such as, **Dylos DC 1700**[48](#ref-northcross_low-cost_2013), **PA-II**,[2](#ref-aq-spec_air_2015) **AirQUINO** by **CNR**[12](#ref-cavaliere_development_2018) reported values of ~ 1.

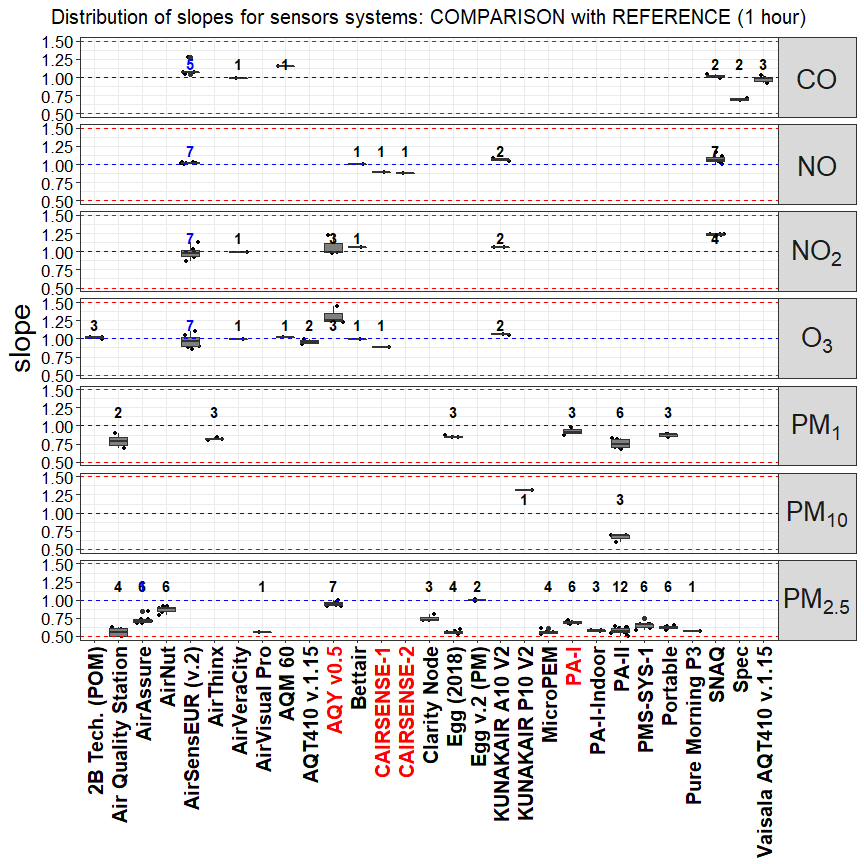
For the evaluation of gaseous pollutants, we found very few OEMs with within 0.7 - 1.0 when using data at at time-resolution of 1 hour. These sensors included the **CairClip O3/NO2** by **CairPol**[23](#ref-duvall_performance_2016),[24](#ref-feinberg_long-term_2018),[57](#ref-spinelle_field_2015),[73](#ref-williams_sensor_2014), the **Aeroqual Series 500 (and SM50)**[24](#ref-feinberg_long-term_2018), the **O3-3E1F** by **CityTechnology**[24](#ref-feinberg_long-term_2018),[26](#ref-gerboles_airsenseur_2015),[57](#ref-spinelle_field_2015),[59](#ref-spinelle_performance_2015) and the **NO2-B43F** by **Alphasense**[64](#ref-sun_development_2017),[76](#ref-zimmerman_machine_2018) (Figure 4). On the other other hand, we found very few records for sensor systems using 24 hour data. As a general remark, we can see that the performance of OEMs sensors is enhanced when they are integrated inside a sensor systems. It is also evident that most of the gathered records from and gaseous pollutants , , and , used 24 hours and 1 hour time-resolution data as required by the European Air Quality Directive.

To check the accuracy of a sensor, when compared to a reference system, we looked at the value of the slope obtained from the linear regression of the sensor measurements against a reference measurement. Most of comparisons were carried out during field tests, while only a limited number laboratory tests were available. Ideally, only an ~ 1.0 and a **slope** ~ 1.0 should be a good indicator of performance for a sensor. Therefore, we only selected records with > 0.7 and **slope** within the range 0.5-1.5.

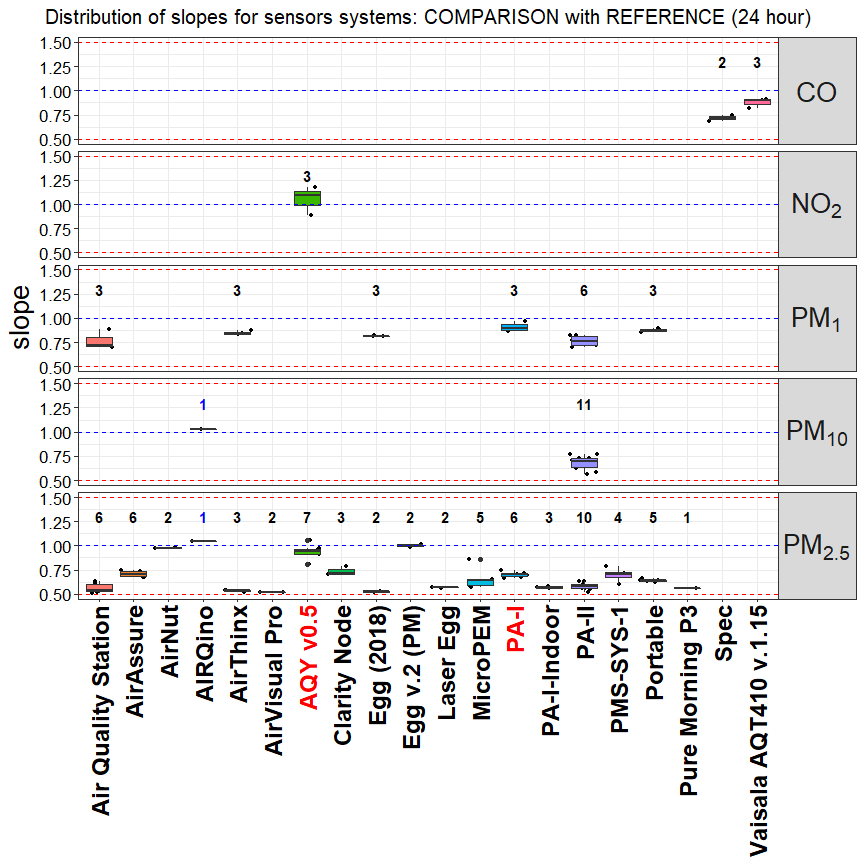
**Figure 7** shows sensor systems such as, the **AQM 60**, the **KUNAKAIR A10 V2**, the **AirSensEUR (v2)** has ~ 1 for most of measured gaseous pollutants when using 1 hour time-resolution data. On the other hand, only few records from sensor systems showed ~ 1 for 1-hour (**PATS+** and **AirNut**) and 24-hour (**AIRQuino**) time-averaged sensor systems. Only few sensors performed well at ideal conditions. Sensor systems such as, **AIRQino**, **SidePak AM510**, **Air Quality Egg (v.2) (PM)**, **Dylos DC1100 PRO**, **AirNut** and the OEM **OPC-N2** were in good agreement with a reference system (Figure 7, Figure 8).

Among OMEs showing ~ 1 when using 1-hour time-averaged data, we found the **SM50**, the **CairClip O3/NO2**, the **S-500**, (, ) and, the **NO2-B4F** () and the **Egg v.2 (PM)** () (**Figure 9**). On the other hand, when using 24-hour time-averaged data, the OEM **OPC-N2** by **Alphasense** and the **Egg v.2 (PM)** by **Air Quality Egg**, shoed slopes ~ 1 when measuring (**Figure 10**).

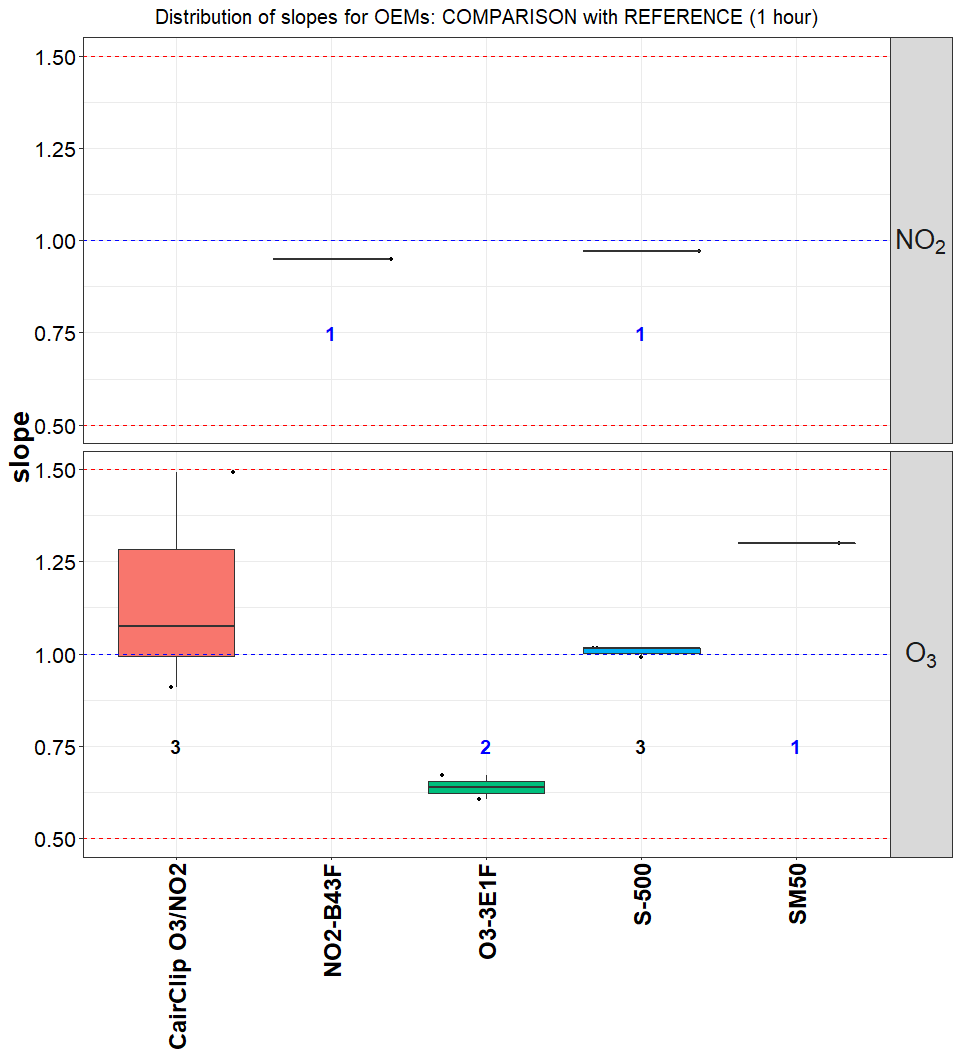
As general remark, from the above analysis we could observe that for some OEMs and sensor systems, the width of the interquartile range IQR ( H-spread) was very narrow. This is an indication of the *reproducibility* of the regression parameters used in their calibration. This becomes relevant when it comes to the development of a reliable sensor system that uses the same OEM sensor and the same calibration algorithms. From the present analysis,



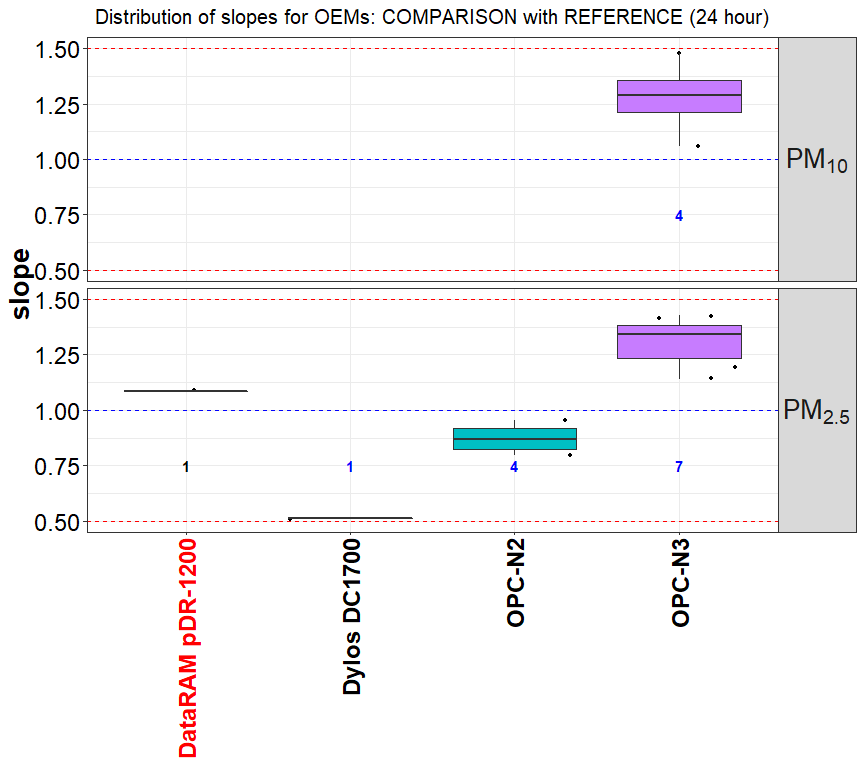
**Figure 7.** Distribution of slopes from the comparison of sensors systems against the reference. Only records with > 0.7 and 0.5 < slope < 1.5 are shown. Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.



**Figure 8.** Distribution of slopes from the comparison of sensors systems against the reference. Only records with > 0.7 and 0.5 < slope < 1.5 are shown. Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.



**Figure 9.** Distribution of slopes from the comparison of OEMs against the reference. Only records with > 0.7 and 0.5 < slope < 1.5 are shown. Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

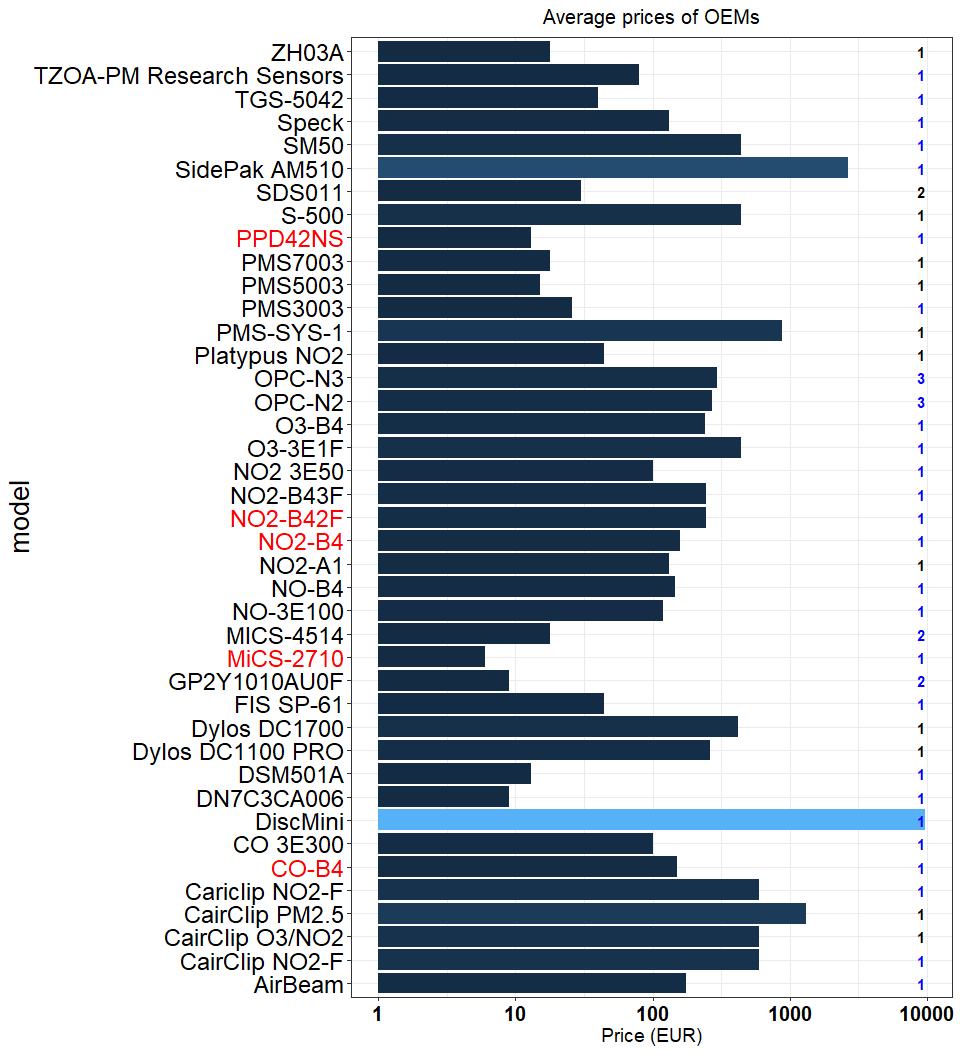


**Figure 10.** Distribution of slopes from the comparison of OEMs against the reference. Only records with > 0.7 and 0.5 < slope < 1.5 are shown. Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

## 6. Price of sensors

As preliminary outcome of the present analysis, we have started identifying sensors systems that are in good agreement with reference instruments commonly used to monitor pollutant concentrations. Although the sensor market constantly develops, we decided to identify a sensor system that is commercially available or that can be assembled with commercially available OEM sensors.

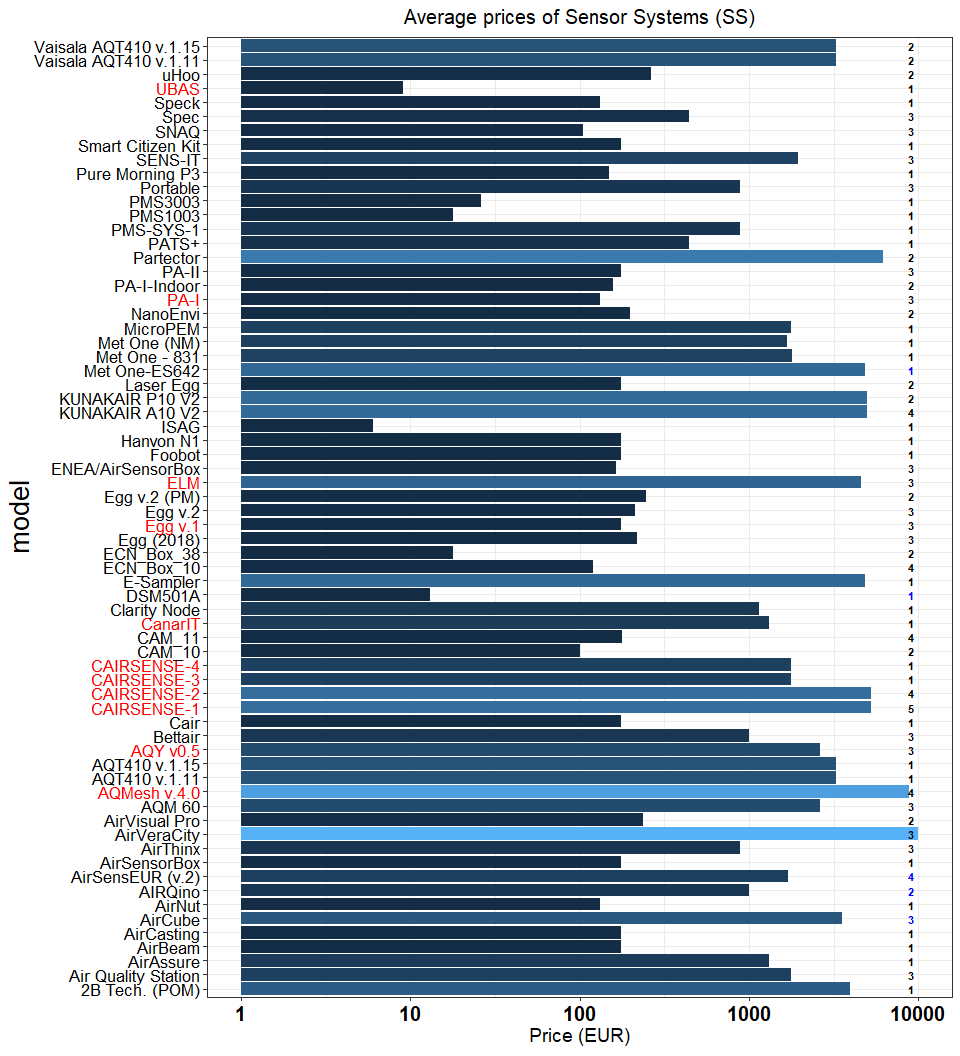
Usually, the price of OEM sensors only represents a small fraction of the selling value of the entire sensor system. In the common understanding, a sensor for air quality is classified as low-cost when its price is less than 10000 EUR. In addition, if a low-cost sensor can measure multiple pollutants, potentially it could be used by local authorities as complementary source of air quality data as subsitute of reference instruments whose cost might rise up to one order of magnitude.



**Figure 11.** Prices of OEMs available on the market (Numbers in bold indicates the number of pollutant measured by each sensor. x-axis uses logarithmic scale). Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

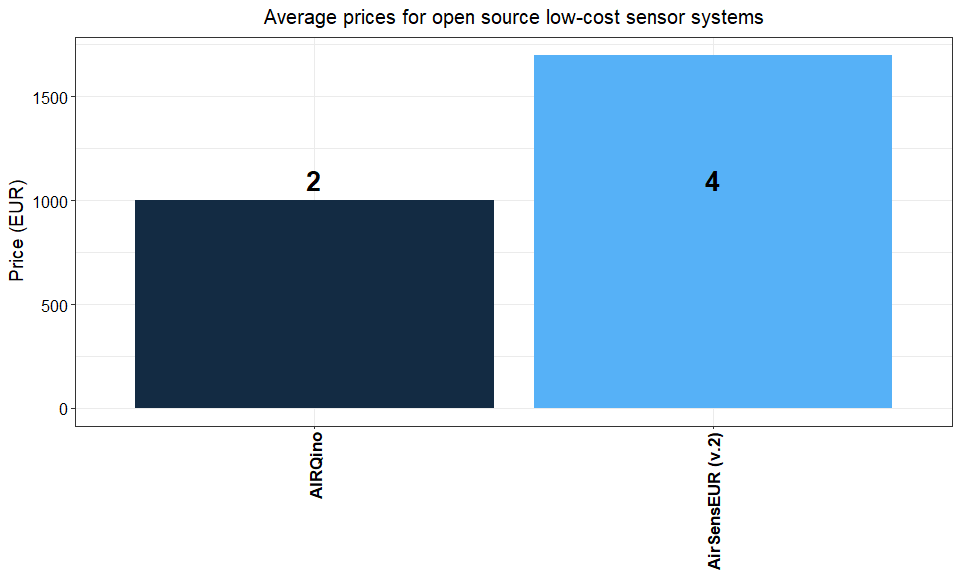
For the evaluation of the price of sensors, we considered all sensor systems manufactured by commercial companies as well as sensor systems built for laboratory testing by research groups. The latter ones are custom-built devices assembled around an OEM sensor. We must to stress out that, while for the detection of different size of particulate matter it is possible to use the same optical sensor, for the detection of gaseous pollutant it is necessary to have a dedicated sensor for each pollutant. Therefore, among all the analysed records, we tried identifying sensor systems that can measure concentration of particulate matter together with gaseous pollutants.

**Figure 11** and **Figure 12** shows the commercial price of OEMs and sensor systems by model and number of pollutant measured by each senso at a price lower than 2500 EUR. As we can see from Figure 12, there is a large number of sensor systems measuring single pollutants. This is an indication about the complexity of having a sensor system measuring both concentration of particulate matter both concentration of gaseous pollutants. On average, we can see that OEMs’s price is much lower of the one of sensor systems. In addition, the price of sensor systems increased together with their capability to measure multiple pollutants. This is because the sensor system may host several sensors to be managed by an electronic board to perform data acquisition.



**Figure 12.** Prices of OEMs grouped by model. (Numbers in bold indicates the number of pollutant measured by each sensor. x-axis uses logarithmic scale). Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

Among the sensor systems measuring multiple pollutants, we could indentify the **KUNAKAIR P10 V2** by **kunak**, the **AirSensEUR (v.2)** by **LiberaIntentio** and the **AIRQuino** by the **CNR** for the detection of , , and and . However,only the **AIRQuino** and the **AirSensEUR (v2)** were the two only sensor systems measuring multiple pollutants and with > 0.7 and 0.5 < < 1.5 when compared with reference systems. Additionally, their commercial price is below the threshold limit defined for low-cost sensors (**Table 8**). We need to point out that, at the date, the **AIRQuino** can measures up to five pollutants (, , , , and , and ), however, only data from PM were available a the time of this review. On the other hand, the **AirSensEUR (v2)** is a complete sensor system that can measure particulate matter and all gaseous pollutants including “ and (radon)”. This sensor system is already operative and has undergone multiple alibrations and filed test where measurements of gaseous pollutants and particulate matter with good agreement with reference measurements.

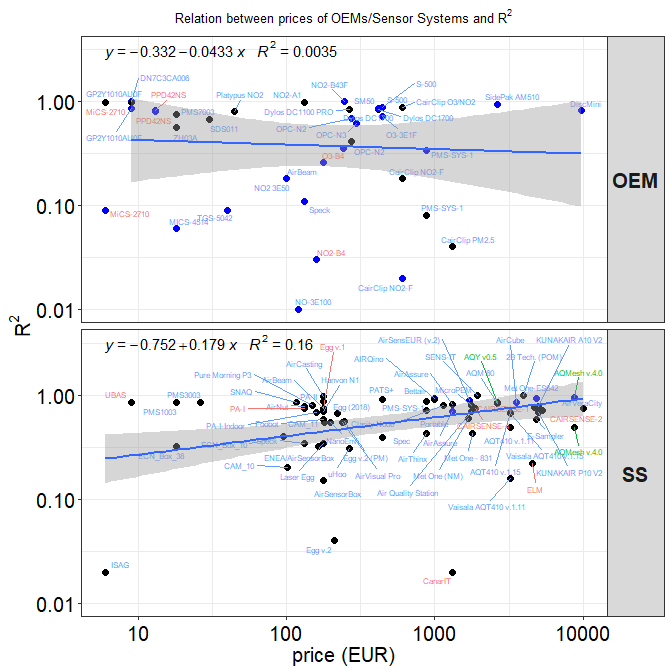


**Figure 13.** Only records with > 0.7 and 0.5 < < 1.5 are shown. Price of low-cost sensor systems (numbers in bold indicates the number of pollutant measured by each sensor).

**Table 8.** Shortlist of sensor systems measuring two or more than pollutants in good agreement with reference systems ( > 0.7; 0.5 < slope < 1.5).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| model | pollutant |  |  |  |  |  | price (EUR) |
| **AIRQino** | PM2.5 | PM10 |  |  |  |  | 1000 |
| **AirSensEUR (v.2)** |  |  |  | NO2 | O3 | CO | 1700 |

As shown in **Figure 14**, we did not find any significative relation between the commercial price of OEM sensors and the value of resulting from the comparison with reference systems. On the other hand, it is possible to observe a increase of the price of sensor systems together with .



**Figure 14.** Relation between prices of OEMs/Sensor Systems (SS) and . Logarithimic scale has been set for both axis. Open source and black box records are indicated with blue and black color, respectively. Names of ‘living’ and ‘non-living’ sensors are indicated in blue and red color, respectively. Fit has been carried out only considering ‘living’ sensors.

The regression equations indicated in **Figure 14** have been calculated only considering “living” OEM / sensor systems. As shown in Figure 14, most of the reviewed sensor systems are “black box” systems. This means that the end-user cannot perform any further correction or re-calibration on the sensor system itself. The relationship observed between the coefficient of determination and the price of the sensor system, it is an evidence that complexity of building a detector for air quality is somewhat linked to the choice of materials, multi-functionality and time-spent to develop a reliable sensor system.

## 7. Conclusions

According to the European Air Quality Directive2, a sensor system can be considered “Equivalent” when it meets the Data Quality Objectives (DQOs) set for data capture and uncertainty3,4 .In order for sensor system measurement to be incorporated into the legal framework set by the Air Quality Directive in Europe, they shall satisfy one of the data quality objectives (DQOs) of the Directive. DQOs, defined as the maximum allowed relative uncertainty, are defined either for reference and indicative measurements or for objective estimations. For inorganic gaseous pollutants, they correspond to 15, 25 to 30 and 75 %, respectively. Although, the objective of sensor systems is to provide the most accurate air pollution measurements, it is most likely that the DQO for reference measurements is out reach while it is believed that by improving the sensor calibration procedures the DQO of “Indicative Measurements” could be met at fixed monitoring sites[35](#ref-key-vocs_metrology_2017).

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