



Review

A Systematic Review of Low-Cost Real-time Air Quality Sensors, Systems, and Evaluation Methods

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Abstract: Air quality and environmental fairness have always been an area of prime interest across the globe. The significance low-cost air quality sensing and practices spikes during the time of pandemic and epidemics when the air becomes a threat to living beings especially human beings. The gradual innovation and enrichment in low-cost air quality sensing sensors, nodes or devices, and systems are exponentially increasing for the last three decades. This work reviews the major contributions in a) low-cost scalable air quality assessment; b) low-cost air quality sensors, sensing approaches and technologies; c) low-cost state-of-the-art gas sensors fabrication methods (MEMS and CMOS); d) low-cost gas sensors measurement configurations and assemblies; e) low-cost air quality sensors calibration and testing systems; f) low-cost air quality measurement evaluation methods and key performance indicators; and g) machine learning-based evaluation for air quality sensors and measurements. A systematic review of past work with a goal to assist end-users, public health facilities, state agencies, researchers, scientists and air quality protection agencies has been rendered in this work. Starting from sensors electrodes to IoT based mobile smart nodes; all have been introduced in this article.

Keywords: Low-cost air quality sensors, air quality assessment, sensing technologies (STs), fabrication, measurement, configurations, sensor assemblies, gas sensors calibration systems (GSCS), evaluation, machine, learning, key performance indicators (KPIs).

1. Introduction

The term “Air Quality” refers to a gas assessment mechanism that can be used as a standard unit variable to govern acceptable pollution in a reciprocal manner as defined per the worldwide health organization (WHO), the U.S. Environmental Protection Agency (US-EPA), and the United Nations Environment Programme (UNEP) [1-3]. An air quality gas sensor is an electronic or electro-chemical instrument that can measure the ratio of gas particles in a given volume of air, usually in units of part per million (ppm), through some sensing element. The air quality gas sensor may also have a variety of other applications [3-5]. In 1815, the first gas detector system known as Davy lamp was invented by Sir Humphry Davy (of England) to detect the presence of methane (firedamp) in underground coal mines [6]. The first gas sensor was invented by Dr. Oliver Johnson that originated from the catalytic combustion (LEL) sensor [7]. Clark and Lyons utilized the strategy of electrochemical detection of oxygen or hydrogen peroxide to measure glucose

in biological samples [8]. The ubiquity of impedance mainly leveraged to realize the gas transducers [9]. The optical sensors are passive, i.e. require external field excitation source to inject some energy into the observation specimen for measurement [10-12]. The feed-back of this energy can have many numerical relationships with the induced signal termed as working response (refractive coupling) [13]. The overall study carried out in this re-search is presented in Fig. 1.

In this paper, the design of air quality gas sensors, their assembly arrays, systems, and the associated methods will be discussed in detail. This will lead to overcome the conceptual challenges that can make it difficult to recognize the similarities and the dif-ferences between existing gas sensing systems and the contributions of new techniques. The contributions of this paper are chronologically comprehended:

1. Scalable low-cost air quality assessment (AQA).
2. Low-cost air quality gas sensor (AQ-GS) technologies.
3. Low-cost commercialized gas sensors fabrication approaches.
4. Low-cost Configurations and topologies.
5. Low-cost Gas sensors calibration and testing systems
6. Evaluation methods or (KPIs) in low-cost air quality sensing;
 - a. Sensing and measurement evaluation parameters
 - b. Calibration evaluation parameters
 - c. Machine-learning evaluation parameters

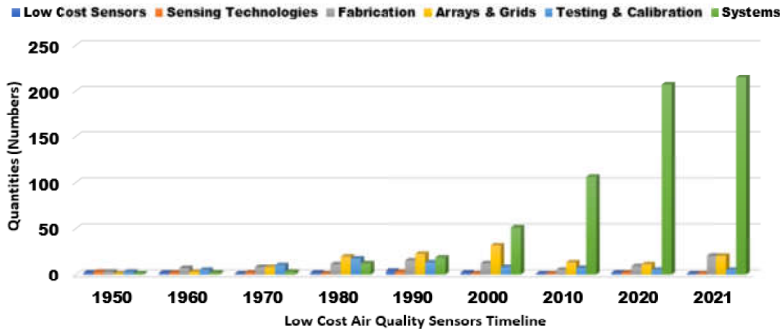


Figure 1. A Chronological Walkthrough of Air Quality Gas Sensors, Methods and Systems [1-177].

In figure 1, the contributions from 1950 to 2021, i.e. last 70 years were focused more with slight theoretical backgrounds in pioneering. In this paper, we will discuss the design of air quality (AQ) sensors, their assembly arrays, systems, and the associated methods in a practical hierarchy presented in figure 2.

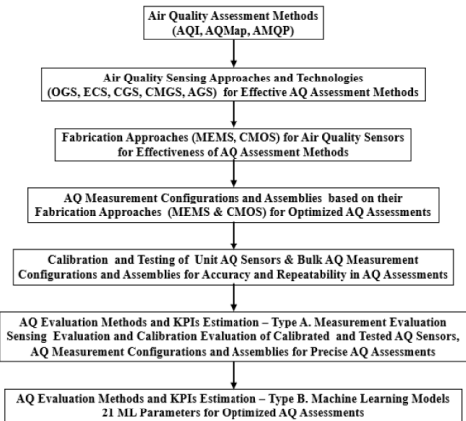


Figure 2. A Practical Hierarchy of Air Quality Assessment, Sensors, Configurations, Fabrication, Calibration, and Evaluation Methods [1-178].

This practice leads to transparency and conceptual challenges that can make it difficult to recognize the similarities and differences between existing gas sensing systems and the contributions of new techniques. The contributions of this paper are chronologically comprehended as: 1) Air quality assessment (AQA) frameworks; 2) AQ sensor types and technologies; 3) state-of-the-art AQ sensors fabrication approaches and technologies; 4) AQ sensors, configurations, and topologies; 5) AQ sensors calibration and testing systems; 6) AQ measurement systems; 7) AQ systems measurement evaluation methods or (KPIs) in air quality sensing.

2. Scalable low-cost air quality assessment (AQA)

In the light of guidance documented by the core environmental protection agencies, WHO, US-EPA, EEA, and UNEP; air quality terminology refers to the entire legislative body of knowledge that involves analysis, methods, and criteria based on air quality [14-17]. The major terms used in this context are:

- 1. Air Quality Index (AQI)
- 2. Air Quality Mapping (AQMap)
- 3. Air Quality Management Plan (AQMP)

Air quality assessment and air crisis risk (ACR) mitigation are strictly sequential and systematic processes. Each phase has its clear and precise significance and contribution in the next phase. AQA and ACR involve estimation of bio-tolerable gas threshold [18,19] such as hazardous gas magnitudes and pollutant ratios in atmospheric volume; geospatial AQA to orchestrate regional AQM [19-22], finally, design a model of regional air volume with effective and contributory variables to provide mitigation plan [23].

2.1. Air Quality Index (AQI)

AQI refers to a structured chart with a bio-tolerable threshold of specific pollutants and bio-hazardous gases recommended by EPA in the area under a specified border agency18-24. The top 10 environmental protection agencies (EPAs) unanimously agreed on the standard of four core gases for outdoor air quality [25] i.e. Ozone (O3), Nitrogen Dioxide (NO2), Sulphur Dioxide (SO2), Carbon Monoxide (CO).

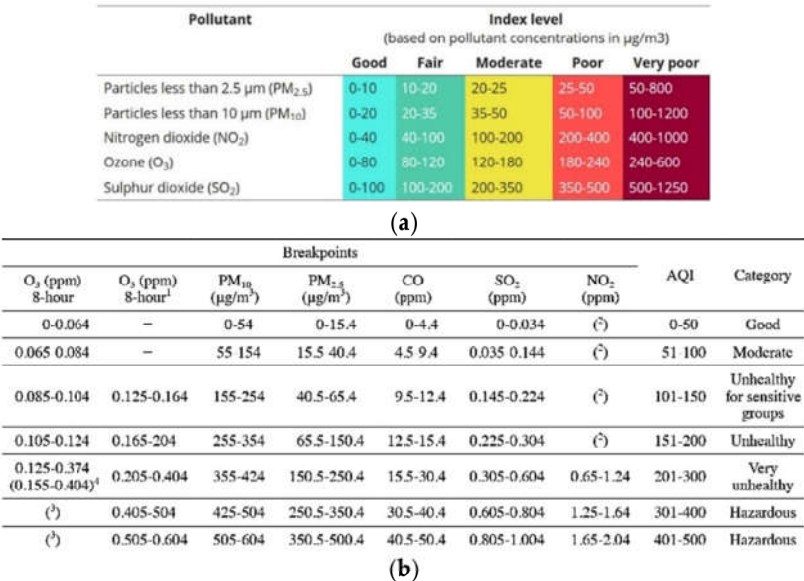


Figure 3. AQI Charts by EEA and US EPAs [21-27] (a) CAQI EEA AQI Cumulative State Chart (b) US EPA AQI Cumulative State Chart.

In figure 3 (a), the concentration of the four gases or the air particles part per million (ppm) constitutes the air quality index (AQI) [26,27] is the fundamental design i.e. the quantities of O₃, SO₂, CO, and NO₂ are the standard gases considered in major environmental standards for AQI. The standard AQI evaluation template for a specific region provided by EEA as Common Air Quality Index (CAQI) and US EPA as AQI are presented in figure 3. The dust pollutants include particulate matter (PM) versions PM-10 and PM-2.5A as standard outdoor AQI with distinguishable cross-sensitivities. In figure 3 (b)The air quality index chart in Fig. 2 presents the mandatory thresholds and limit windows for AQI variables that serve as air pollution index (API). Another multi-parametric AQI innovation in assessment is the environmental performance index (EPI) by Yale Center for Environmental Law and Policy [28].

2.2. Air Quality Mapping (AQMap)

The geo-locations in the vicinity of AQ measurement using collective averaging and mean estimation procedures derive an air quality map with an additional parameter, that is geographical positioning system (GPS) value [29, 30]. The process of collection of all such points and orientating them geo-spatially is called AQM [25-31]. There are two types of AQM: (i) indoor air quality mapping (I-AQM); and (ii) outdoor air quality mapping (O-AQM) [33] in fig 4.

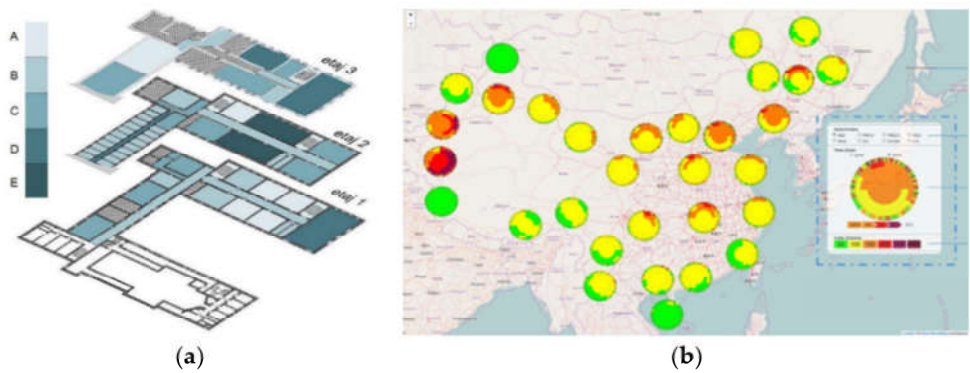


Figure 4. Two fundamental approaches in AQM²⁴⁻³³. (a) Indoor Air Quality Mapping. (b) Outdoor Air Quality Mapping.

Fig. 4, shows that I-AQM is buildings and O-AQM is region-wise. There are different sets of gases and ratios of pollutants with molecular sizes [33]. The charting and graphing as well as typo-graphic presentation schemes available, and their standardization process for AQM based on their relative effectiveness are mentioned in this work [34].

2.3. Air Quality Management Plan (AMQP)

The AQMP or the Brownian motion (Robert Brown) is defined as the random nature of particle dynamics in the air. In the entire assessment of AQ, the most challenging and attention criteria is AQMP, especially air quality modeling [35]. The key work was accomplished by Dr. Gary Haq and Dr. Dieter Schwela in 2008 while modeling the toughest regions in Asia [36, 37]. Claudia et al. presented a very appreciable work in virtual pollution modeling using Bayesian network theory [38]. The AQMP (2012) presented by Dr. Bjarne Sivertsen and Alena Bartonova holds a landmark value in regional level AQMP [39]. The INDAIR model and clean energy were focused on bounded value models for a clear interpretation of decision making AQMP parameters [40, 41].

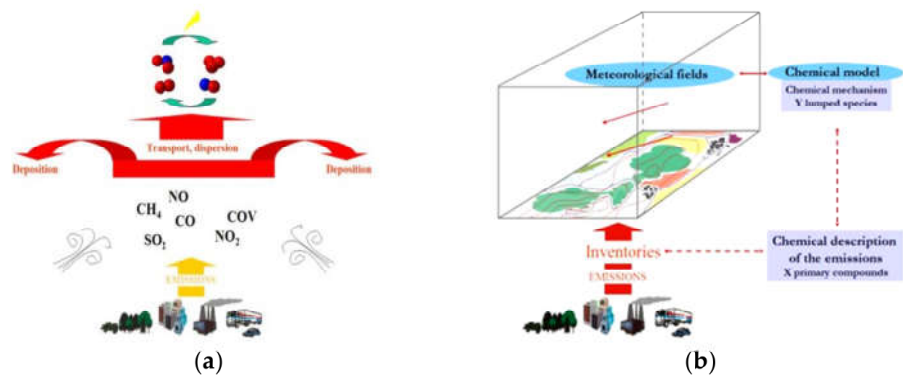


Figure 5. Two Step AQMP Methodology Practices in AQM [18-41] (a) Air Quality Modelling. (b) Air Quality Management Implementation Scheme.

3. Low-cost air quality gas sensor (AQ-GS) technologies.

There are five approaches to sense in air quality measurements and their architectures and presented in Fig. 6 [44].

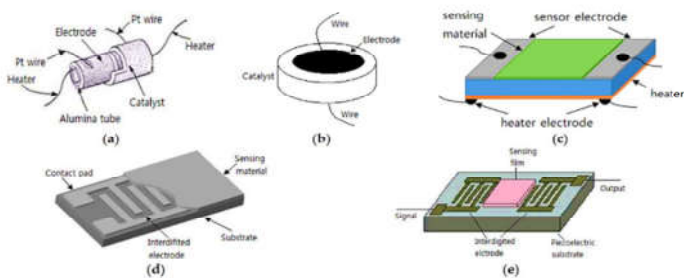


Figure 6. Five Primitive Approaches in AQ Gas Sensors Technologies [44]

Furthermore, there are five unique technologies in low-cost air quality gas sensors (AQGS): a) Optical Gas Sensors (OGS); b) Electrochemical Gas Sensor (ECS); c) Capacitive Gas Sensor (CGS); d) Calorimetric Gas Sensor (CMGS); and e) Acoustic Gas Sensor (AGS) [33-48]. The architectural and working principles are explained in detail in the respective sections.

3.1. Low-Cost Optical Gas Sensors (OGS)

The AQMP or the Brownian motion (Robert Brown) is defined as the random nature of particle dynamics in the air. In the entire Identical or isometric coupling by 1:1 Tx/Rx is a combination of transmitting and receiving mode. In this case, a variable dielectric like the human body is introduced as exhibited in Fig. 6 [49, 50].

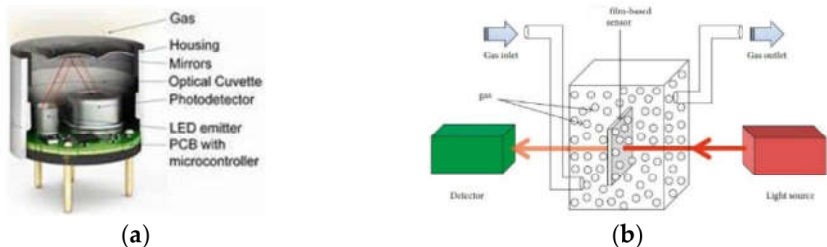


Figure 7. Overview of OGS [49,50]. (a) Architecture. (b) Working Principle.

In Fig 7, a light source transmits a light array through a file-based sensor that measures the impact of light on air particles and returns an analog voltage value for every

unique gas which is cycling through micro-OGS the chamber. The widely used OGS is non-dispersive infra-red (NDIR) gas sensor that has a swift response and long lifetime as this type does not use any consumables. The NDIR-GS is presented in Fig. 8 below [49-51].

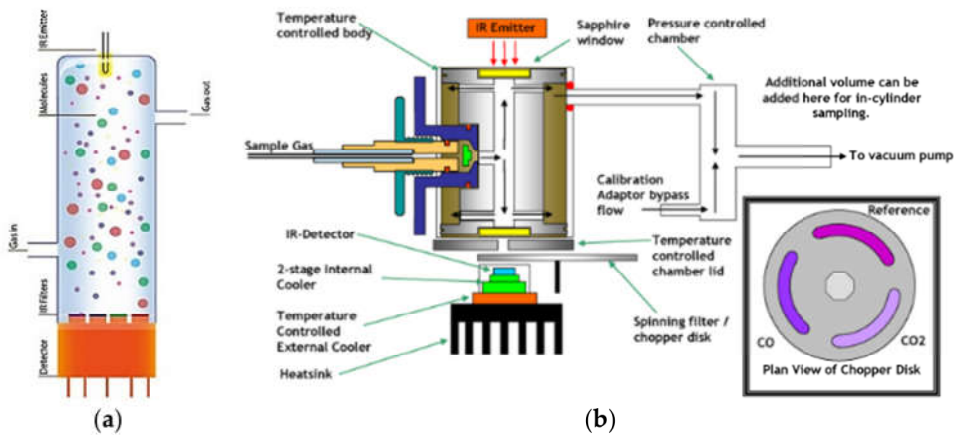


Figure 8. Overview of NDIR-GS [51] (a) Architecture. (b) Working Principle.

In NDIR-GS presented in Fig. 8, the same principle is used, i.e. light emission and reservation, the only difference is the IR nature of light that can sense up to $0.1\text{ }\mu\text{m}$ particles [51].

3.2. Low-Cost Electrochemical Gas Sensors (ECS)

In ECS, the receive mode can possibly be made by making the working electrode as sensing element and counter electrode as an extension of the transmitting electrode to pick transmitted electrons through the electrolyte [52-54]. In this case, a working electrode acts as a multi-channel receiver for multi-variable sensing as exhibited in Fig. 9 below [53].

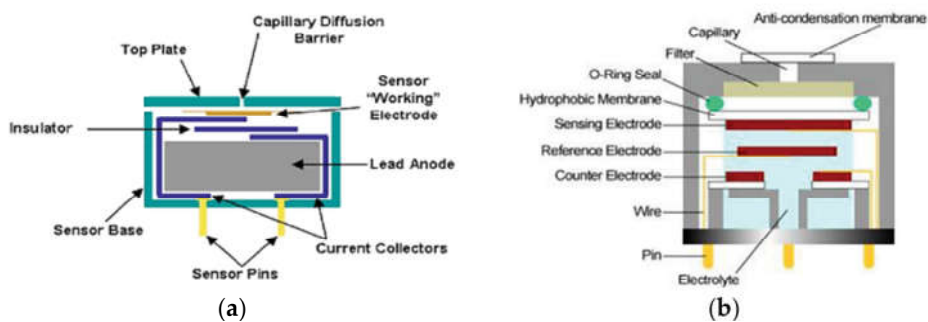


Figure 9. Overview of ECS [52, 54] (a) Architecture. (b) Working Principle.

The ECS-GS presented in Fig. 8 is a generic ECS architecture used by leading vendors in the gas sensors industry, i.e. FIGARO, SGX, and Honeywell. The faster response rates and solid-state architectures are presented in [54, 55] needs fabrication tendering to assess their mass production feasibility over existing technologies.

3.3. Low-Cost Capacitive Gas Sensors (CGS)

In CGS, the transmit mode is made possible by making the sensor body an extension of the transmit electrode (or capacitor) to improve the nearest transmitter created electric fields⁵⁷. In this case, a gap volume acts as a multi-impedance transmitter for multi-variable sensing receivers as presented in Fig. 10 (a) below [58].

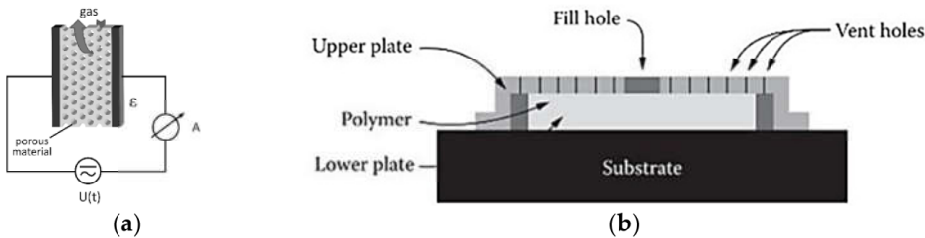


Figure 10. Overview of CGS [58]. (A) Architecture. (B) Working Principle

In Fig 10 (b), it is shown that CGS is merely a capacitor in an isolated circuit where the electric flux between the plates is the volume for gas measurement. The fill hole allows the air to enter the sensing zone and cycles back to the atmosphere through vents.

3.4. Low-Cost Calorimetric Gas Sensors (CMGS)

In CMGS, a displacement current flows through the body to ground through a catalyst loaded electrode gap [60]. A single electrode is utilized as a transmitter and receiver of flux as exhibited in Fig. 10 below [61-62].

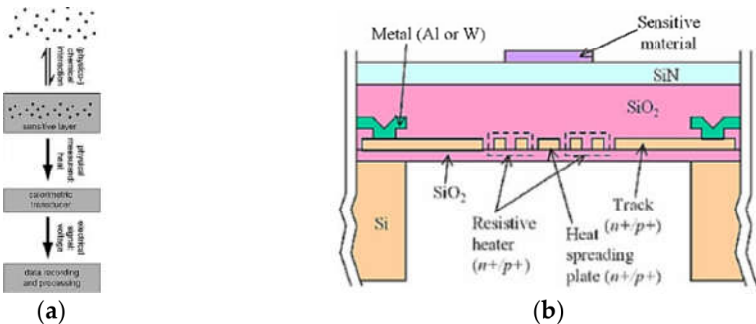


Figure 11. Overview of CMGS [58]. (A) Architecture. (B) Working Principle

The finite element methods (FEM) used by Mohamed Serry et al. was a successful demonstration of a unique signal at different heater temperatures which could be increased more than 23 times by increasing the heater voltage from 3.5 to 5.0 V. Selectivity versus acetone vapor was also experimentally verified [63].

3.5. Low-Cost Acoustic Gas Sensors (AGS)

In AGS, a displacement or acoustic wave is transmitted through the gas and the difference in the characteristics of the received wave from the original wave is converted into an equivalent AGS value [64, 65]. A single electrode is utilized as a transmitter and receiver of flux as exhibited in Fig. 12 below [64-66].

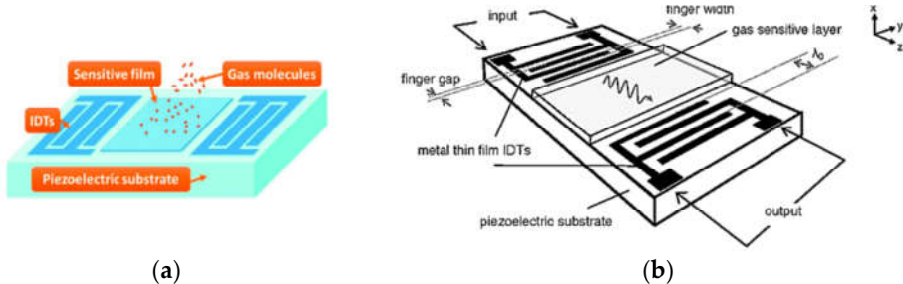


Figure 12. Overview of AGS [58]. (A) Architecture. (B) Working Principle

The new dimension in AGSs was explored in 2018 by Xueli Liu et al. According to Xueli et al, a typical surface acoustic wave (SAW) gas sensor described in Fig. 11 has a

core element of thin-film coated along the SAW propagation path between the two inter-digital transducers (IDTs). The absorption in sensitive thin-film modulates the SAW propagation by a so-called mass loading, viscoelastic or acoustic-electric effect, depending on the physical class of the sensitive thin-film itself [67].

4. Low-cost Commercialized Gas Sensors Fabrication Approaches

A comprehensive work in micro-fabrication of gas sensors was accomplished by Jan et al. in [68] where different industries, based on multi-type gas sensors and their effective fabrication methods, were elaborated. The acoustic; carbon nano-tube (CNT); electro-chemical; fiber-optic; metal oxide semiconductor (MOS); organic-based chemi-resistive; piezoelectric; photonic crystal gas sensors and volatile organic compound (VOC); sensors fabrication was categorically addressed in their works [69]. The most recent studies [68-73] highlighted only two state of the art fabrication approaches for the Gas Sensors (GS):

1. Micro-Electro-Mechanical Systems (MEMS) Fabrication Approaches
2. Complementary Metal Oxide Semiconductor (CMOS) Fabrication Approaches

4.1. Micro-Electro-Mechanical Systems (MEMS) Fabrication Approaches

The MEMS was the first of the commercialized approach for CE's fabrication and was composed of 15 core steps as shown in Fig. 13 for the first steps in gas sensing as electrode fabrication and placement. The molybdenum micro-heaters were prepared in the following steps [74]: a) the membrane micro-heater utilized 104 mW to acquire an 800 °C with a thermal resistance of 7.2 °C/mW; b) FLIR camera was used to acquire thermal distribution patterns overheating area; c) a temperature gradient of 1.18 % to its periphery; d) stabilities of the micro-heated were analyzed (mechanically and chemically as well its membrane failures safety threshold was estimated; e) the characterization of micro-heater using optical profile-meter was estimated to be 16.25 µm at 800 °C.

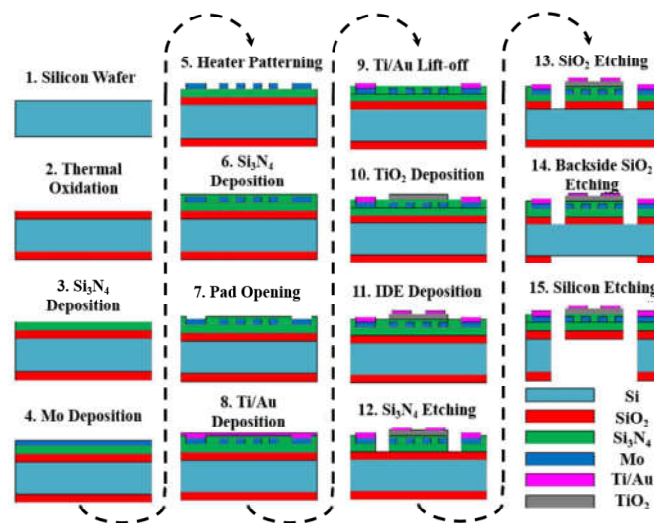


Figure 13. The Fifteen Step MEMS Fabrication Process for GSs [75]

In Fig. 13 the entire MEMS fabrication process flow of the electrode can be observed. The pulse train and the constant DC voltages were also characterized in [74]. The response time is in the order of 19ms and the recovery time is equal to 34 ms. A stable temperature was exhibited by a micro-heater with a negligible resistance drift (0.96%) for 600 hours. The accuracy of CO was (5000 parts-per-billion (ppb)) measured between 300 to 700 °C. Another MEMS process for ECGS based on micro-heaters are using SiO₂ with sputtering

of a 10/60 nm were coated with thick Ti/Pt metal layer of 300nm thickness of a 10/60 nm Cr/Au layer [75].

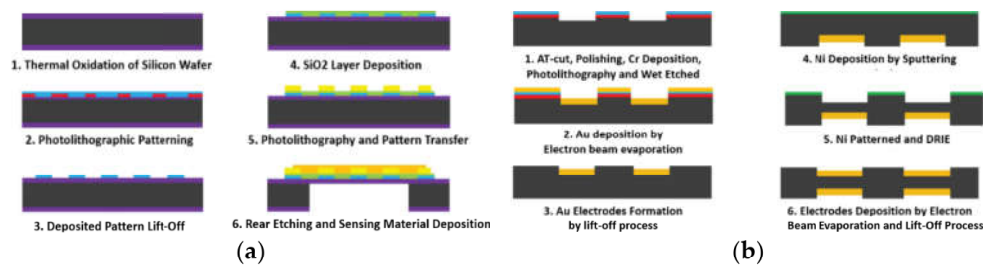


Figure 14. Two Six-Step Electro-chemical gas sensors (ECS) fabrication by MEMS Fabrication Approaches [75-79] (A) RIE Method [74,75]. (B) Au Electrodes [76-79]

In Fig. 14, it can be noticed that the AGS (quartz crystal micro-balance) was manufactured on a 168 μm to 330 μm and a diameter of about 5 mm to 25 mm quartz [77]. Gold (Au) and Platinum (Pt) were used as electrodes. Each quartz was etched using RIE. An anisotropic and inductively-coupled plasma reactive ion etching (ICP RIE) method can be used with etch quartz [78]. Deposition, lift-off, photolithography, beam evaporation, Ni patterning were the major processes employed in these methods [79]. The capacitive micro-machined ultrasonic transducer gas sensor has also been introduced as an exemplary case of MEMS fabrication in 12 sequential steps for AGS given in Fig. 15 [80, 81].

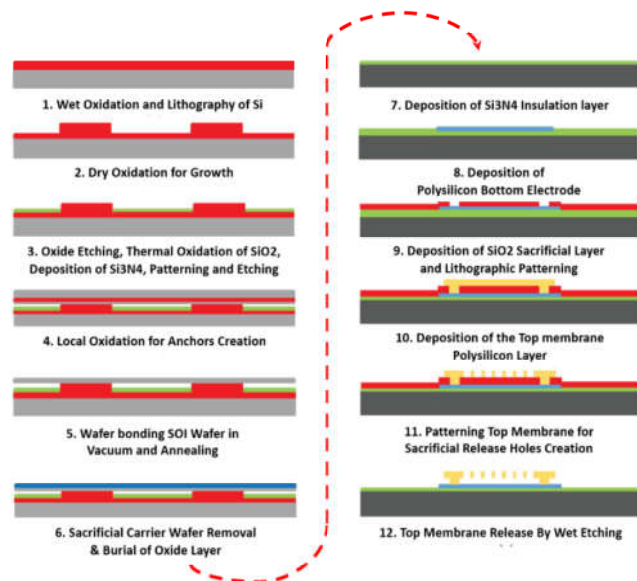


Figure 15. The Twelve Step MEMS Fabrication Process using Si [80-85]

It is eloquent from Fig. 15 that in MEMS fabrication is mainly dependent on the coating, sputtering, exposure, electroplating, and photolithography. One of the state-of-the-art methods was the sacrificial method and wafer bonding [80-85], i.e. utilizing the cavity flow for sensing in first and trapping air in second.

4.2. Complementary Metal Oxide Semiconductor (CMOS) Fabrication Approaches

The current CMOS fabrication approaches mainly cover field-effect transistors (FETs) using Silicon on insulator (SOI) technology [86-90] for GSs is CMOS based and its primitive impedance model and assembly are presented in Fig 16 [87].

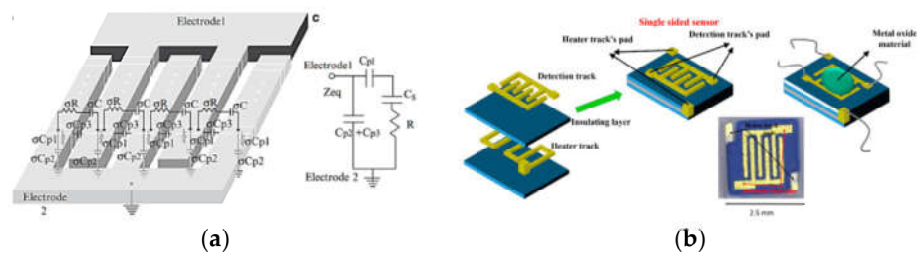


Figure 16. CMOS Realization of GS and its Post Fabrication Assembly (a) Impedance Model and Dye Realization [35, 56] (b) Sensor Assembly (LoC) [35, 56-58]

The entire CMOS electrode microchip cluster is resolved into finite elements and is equivalent to a capacitance and a resistance between electrode 1 and electrode 2 [86-87]. The CMOS capacitive electrode-based sensors assembly of manufactured GSs is presented in Fig. 16.b. The CMOS fabricated FET sensors are nano-capacitive types in a vast sense and are presented in Fig. 17 and Fig 15. The Twelve Step MEMS Fabrication Process for GSs is presented in the following references [80-85].

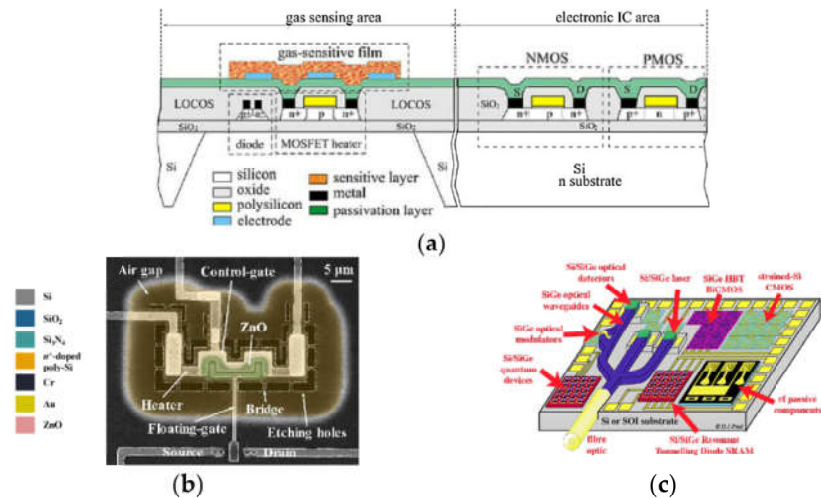


Figure 17. Major FET Gas sensor architectures using CMOS Approach (a) Schematic of a Cascaded MOS-FETs coupled with IC area with Si Substrate [87] (b) Detailed view of a FET based Gas Sensor [86-88] (c) Complete FET Sensor Assembly [86-89]

The three major features of the sensors presented in Fig. 17 from [35, 56-58, 86-90] were able to deliver the response rates of less than 3 seconds and with a resolution of ppb. The SOI technology used in the FETs (from Fig. 17) is produced through the CMOS process (Fig. 18) detailed in [91].

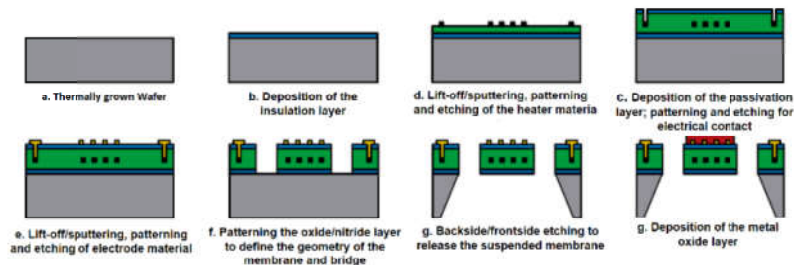


Figure 18. Process of Fabrication of Monolithic GS by CMOS technology [91]

For wet etching Tetra-methyl-ammonium hydroxide (TMAH) was used being fully compatible with CMOS processes [90-92]. The deep reactive-ion etching (DRIE) in such a case

was used for miniaturization of the sensor [91]. The layered deposition of the SOI technique enabled fabrication at 400 to 600C with lowering the leakage current [92-94].

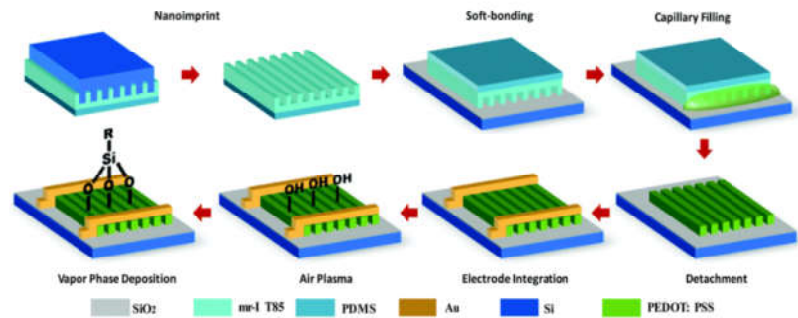


Figure 19. Process of DRIE based SOI Fabrication of Monolithic GS by CMOS technology [92-94]

The most recent work [95] in Mar 2020 by Yiang et al. is the state of the art in the entire generation [96-100] of CMOS nanofabrication based on nano-wires and nano-electrode deposition. The E-Nose term is often used for nano-scale fabrication in CMOS with multi-sensor electrode integration over a single dye [95]. The soft-lithographic technique for chemo-resistive gas sensor array fabrication with ordered sub-100 nm wide conducting polymer nanowires (poly-ethylene-dioxythiophene). The poly (styrene sulfonate) (PEDOT: PSS) functionalized in an assembly of different self-assembled monolayers (SAMs) were able to measure VOCs at ppb.

5. Low-cost AQ Measurement Configurations and Assemblies

Smart methods like machine learning and data analysis for AQA processes require the gas sensors to be in specific format or topology for accuracy, effectiveness, and trust-able measurements [101-108]. There are two core multi-gas sensing or sensor topologies (also called electronic nose) arrays and grids, further elaborated as; a) Gas Sensor Arrays and Grids based on System on Module (SoM) Approach; b) Gas Sensors Array on Chip based SOI.

5.1. Gas Sensor Arrays and Grids based on System on Module (SoM) Approach

The term electronic nose board (ENB) was used by various researchers across the world for a specific multi-sensor heterogeneous instrumentation PCB (Figs. 20 and 21) from [103-109]. The orientation of ENBs is for a typical sensing application is called gas sensing array (GSA) or GS grid (GSG) [102]. The multiple GSAs send data to a central data acquisition collector or gateway called GSG [104]. Different GSAs and GSGs from novel works were objectively discussed in [103-109].

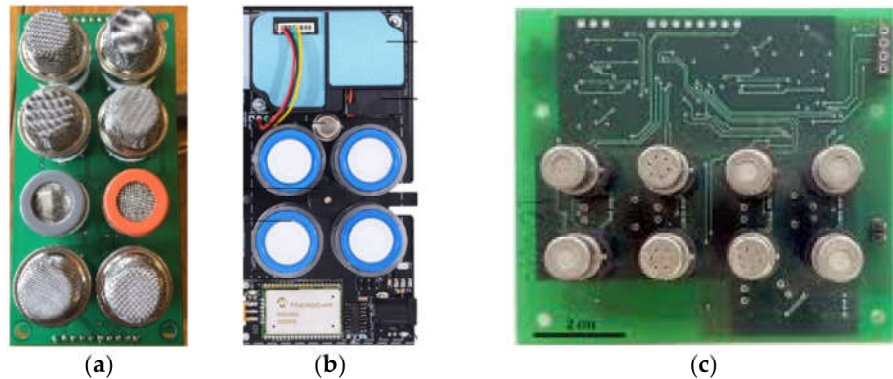


Figure 20. Major contributions in Applied GSGs and ENBs. (a) Trio GSG for I-AQA [107]. (b) Wound Infection ENB [108] (c) Smart Rig Test ENB [109].

Gradient descent method was used to detect food ripening by GSA interfaced with STM32 in Fig. 20 (a) [103]. Later outdoor air quality assessment was forecasted by GSA in Fig. 20 (b). Similarly, the water filtration assessment was performed using particle swarm optimization (PSO) by 8 MOX GSA boards formed a GSG interfaced with MSP430F247 board as presented in Fig. 20 (c) [105-106].

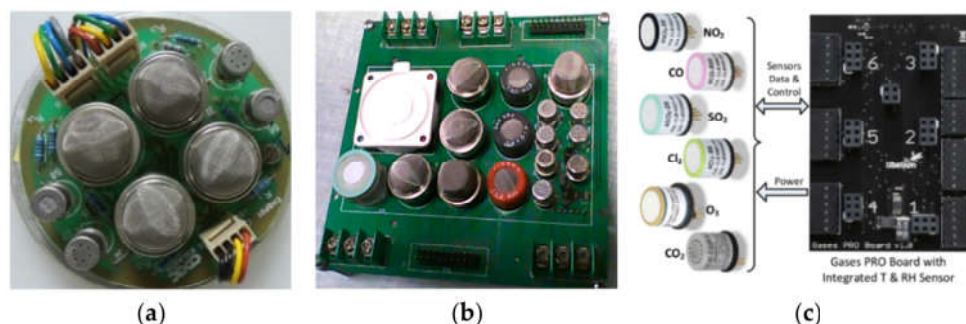


Figure 21. Major contributions in Applied GSGs and ENBs. (a) Trio GSG for I-AQA [107]. (b) Wound Infection ENB [108] (c) Smart Rig Test ENB [109].

I-AQA was performed in a hospital using least square estimation for HVAC testing using Trio GSG [107], i.e. the 8 indoor gases were assessed from figure 20 (A). In figure 21 (B), the SVM was used to assess wound infection by ENB based on 4 types of sensors [108]. In April 2020 the most recent ENB was used for assessment of MFCs in a gas sensors calibration test bench [109] presented in Fig. 21 (C).

5.2. Gas Sensor Arrays and Grids based on System on Module (SoM) Approach

In 2019-2020, state of the art appeared in the market as GSA on Chip, the next step in Sensor on Chip prepositions [110-113]. These arrays delivered accuracy at details of ppb. In 2016, Screen Printed Electro-chemical (SPEC) sensors shrunk this gas sensing technology down to a size appropriate for consumer devices that can be made at the volumes and costs suitable to the mass market [110] in Fig. 22 (a). The multi-sensor chip was proprietary as Digital Sensor Platform on Chip (DSPoC) and the overall ENB was called Open Source DSPoC Kit.

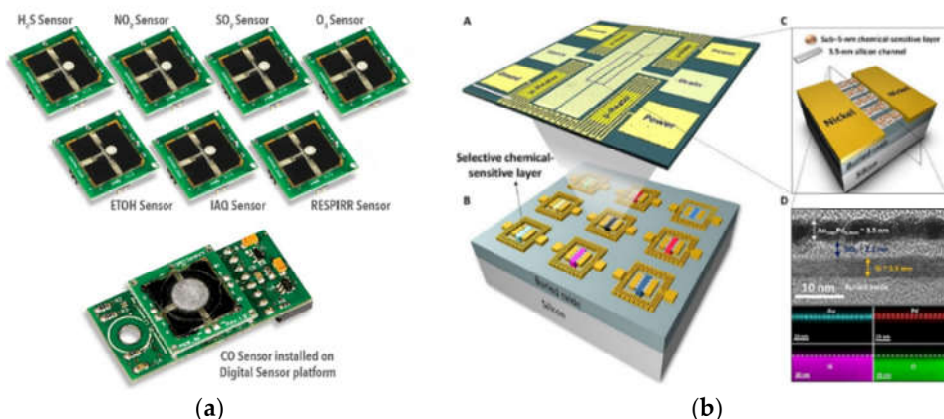


Figure 22. Major contributions in GSAoC based SOI for Applied GSGs and ENBs. (A) SPEC DSPoC with GSA on Chip [110]. (B) Monolithic GSA on Chip with 3.5 nm wires [111].

In 2017, H₂S, H₂, and NO₂ gases were sensed using a novel GSAoC with 3.5nm wires [111]. The most recent work was Single-Chip Gas Sensors Array (SC-GSA) in which a set of four micro-heaters were used to access a single suspended SiO₂ diaphragm [112], using thermal proximity and achieved low power consumption (~10 mW for 300 °C). The

plasma optimized thin films of ZnO, BaTiO₃-CuO doped with 1% Ag, WO₃, and V₂O₅ are employed for selective sensing of CO, CO₂, NO₂, and SO₂. The four sensors were controlled independently and demonstrated CO (~78.3% for 4.75 ppm) at 330 °C, CO₂ (~65% for 900 ppm) at 298 °C, NO₂ (~1948.8% for 0.9 ppm) at 150 °C, and SO₂ (~77% for 3 ppm) at 405 °C operating temperatures. The complete implementation for GSAOC is the current state of the art [113].

6. Low-cost Calibration and Testing of AQ Gas Sensors

In 2009, the first structured gas sensors calibration system was designed and implemented by a measurement calibration system that was developed by Octavian et al. [114]. A standard AQS Calibration follows the [114] schematic as: a) An Air-sealed chamber with inflow and outflow valves; b) mass flow controllers (MFCs) for the desired concentration of gas from a cylinder or a PID controller gas flow loop; c) gas cylinders with different concentrations; d) temperature actuator (heater); e) humidity actuator (steam regulator); f) gas collectors for the environmental model; g) measurement instruments other than gas sensors for comparison interfaced with a computer. The recent work realized a plethora of efforts made in gas sensors calibration [114-127] presented in Figs 23-26.

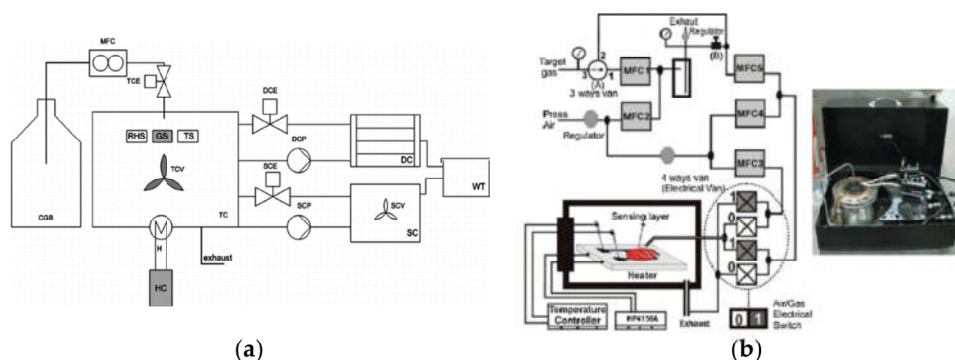


Figure 23. The AQ gas sensor calibration chamber-based system. (a) P&ID of a Unit AQGS Testing and Calibration System [114]. (b) System Assembly and Architecture [115].

In Fig. 23 (a), an industry-standard instrumentation topology, i.e. piping and instrumentation diagram (P&ID) is presented for AQGS [114]. It consists of 14 components: 1) CGB: Calibration gas bottle; 2) MFC: Mass flow control; 3) TCE: Testing chamber electro-valve; 4) DCE: Drying chamber electro-valve; 5) SC: Saturation chamber electro-valve; 6) DCP: Drying chamber pump; 7) SCP: Saturation chamber pump; 8) DC: Drying chamber; 9) SC: Saturation chamber; 10) HC: Heater control; 11) H: Heater; 12) WT: Water tank; 13) TC: Testing chamber ventilator and 14) SCV: Saturation chamber ventilator.

The chamber ventilator's internal architecture varies with the sensing technology detailed in a survey on gas sensing (Xiao Liu et al. [115]). The two studies in testing performance of field gas sensor calibration techniques were proposed by Joanna et al. [116] for Colorado. The characterization study conducted by Leidinger et al. led to a new horizon in test gas generation systems [117]. In Fig. 23 (b), an experimental gas sensor test, and calibration system by for SnO₂ nanowires based gas sensors are presented (Le Viet Thong et al. [118]). The test was performed by measuring all the sensors with liquid petroleum gas (LPG, 500–2000 ppm) and NH₃ (300–1000 ppm) at different temperatures (50–450 °C) using a set up with high speed switching gas flow (from/to air to/from balance gas). Balance gases (0.1% in air) were purchased from Air Liquid Group, Singapore. The system employed a flow-through with a constant rate of 200 sccm. The miniaturized environmental control chambers presented in Fig 24 were introduced by Yi Chen et al. [119] and Jordi Follonosa et al [120].

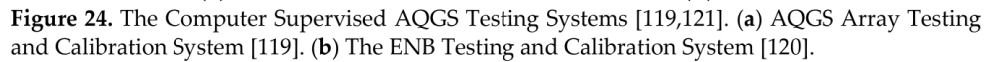


Figure 25. The Controlled Environment Heterogeneous AQGS Testing Systems [119,121]. **(a)** AQ GSA Testing and Calibration System [121]. **(b)** Air Quality Mesh Network Testing and Calibration System [122].

In 2020, the most recent state of the smart gas sensors calibration test rig appeared in literature by Mohieddine A. Benammar et al. [122] presented in figure 25 (a). In fig 25 (a), Smart TestRig took account of all the major improvements recommended in studies by Maag, B. et al. [123] for gas sensor calibration in air monitoring deployments. Spinelle, L. et al. [124] present field calibration of a cluster of low-cost available sensors for air quality monitoring using O3 and NO2. Mijling, B. et al. [125] worked on field calibration of electrochemical NO2 sensors in a citizen science context. Hagan et al. [126] present calibration and assessment of electrochemical gas sensors by co-location with regulatory-grade instruments; Hasenfratz, D. et al. [127] for on-the-fly calibration of low-cost gas sensors; Yang, F. et al. work [128] introduced dynamic calibration of electrochemical gas sensors for accelerated analytic quantification; Tian, B. et al. [129] proposed an environment-adaptive calibration system for outdoor low-cost electrochemical gas sensors. In fig 25 (b), Arvind et al. [121] performed the entire testing and calibration of several gas sensors using a custom sensing chamber (volume ~300 cm3), PID controller electric heater. The gases were individually mixed with dry synthetic air and introduced inside the test chamber at the controlled flow rate of 50 cm3/min. One of the core innovations in this work was an evacuation pump scheme with 8×10^{-1} Torr using a rotary vacuum pump. In the next generation, testing calibration systems curve fitting and error proportionalities performed for porous silicon filled Pd/SiC nano-cauliflower thin films for high-performance H2 gas sensors as an example by Arvind Kumar et al. [121] presented in Fig 25 (b).

7. Low-cost AQ Evaluation Methods and KPIs Estimation

The AQ evaluation methods define the credibility of AQ sensing and data abstraction. or machine learning models [140]. It has two sections: a) multi-parametric sensing evaluation; b) statistical calibration evaluation; and c) AQ ML model evaluation.

7.1. Multi-Parametric Sensing Evaluation

The protocol for AQ sensing or measurement is a set of parameters that assist in decision making for decision making and further data analysis [141]. The key performance indicators (KPIs) for this evaluation are: response time, accuracy or error-gradient, standard uncertainty, interferent uncertainty, temperature effect, pressure effect, linearity, precision, bias, repeatability, stability, sensitivity, the limit of detection (LOD), interferences or cross sensitivities such as NO2 and O3, or PM and relative humidity, root-mean-square error (RMSE), and determination coefficient (R2) [142]. From global AQ evaluation contributions to date there are 15 KPIs [143-148]. Let R_s be the sensor response, x and y be the measured values, and a, b , are the parameters of the orthogonal regression. The KPIs are given as: i) Sensor repeatability (S_r); ii) Correlation coefficient (r); iii) Average short term stability (D_{ss}); iv) Fractional bias (FB); v) Average long-term drift stability (D_{ls}); vi) Mean absolute error (MAE); vii) Response matrix (D_{matrix}); viii) Factor of exceedance (FOEX); ix) Interferant quantity ($Y_{int,z}$); x) Normalized mean-square error (NMSE); xi) Standard uncertainty of interferent $\mu(int)$; xii) Temperature effect ($E_T(R_s)$); xiii) Sum of square of the relative residuals (RSS); xiv) Mean bias error (MBE); xv) Root-mean-square error (RMSE). The mathematical and semantic details for the mentioned parameters are given in Table 1.

Table 1. Multi-parametric Sensing Evaluation Parameters.

Parameters	Symbol	Mathematical Description	Characteristics/Role
Sensor repeatability	S_r	$\sqrt{\frac{\sum (R_1 - \bar{R})^2}{N - 1}}$	The repeatability of the sensor's response shall be evaluated by calculating the standard

			deviation of sensor values for 3 consecutive averaging time-periods when the sensor is exposed to zero gas and 80 % of LV under repeatability conditions.
Correlation coefficient	r	$\frac{\frac{1}{n} \sum_{i=1}^n ((M_i - \bar{M})(RM_i - \overline{RM}))}{\sqrt{\frac{1}{n} \sum_{i=1}^n ((M_i - \bar{M})^2 \sum_{i=1}^n (RM_i - \overline{RM})^2)}}$	Measures the strength and the direction of a linear relationship between two variables and receives a value between 1 and 1; is independent of the difference in the variance (var) of M and RM, thus if $r=1$ and $\text{var.}(M) < \text{var.}(RM)$, then variance correction may be required.
Average short-term stability	D_{ss}	$\frac{\sum_1^{N-9} R_{s,after} - R_{s,berfore} }{N - 9}$	used to estimate the contribution of the short-term drift to the measurement uncertainty of sensors.
Fractional bias	FB	$\frac{\mu_M^2 - \mu_{RM}^2}{\frac{1}{2} (\mu_M^2 + \mu_{RM}^2)}$	Represents a measure of the agreement between the mean measured concentrations against the reference measurements. A perfect agreement would imply that $FB=NMSE=0$.
Average long-term drift stability	D_{ls}	$\frac{\sum_1^{N-3} R_{s,after} - R_{s,berfore} }{N - 3}$	used if the stability is different at different test gas levels.
Mean Absolute error	MAE	$\frac{1}{n} \sum_{i=1}^n M_i - RM_i $	Indicates the average of the magnitude of the errors; it does not indicate the direction of the error, but only its magnitude and it's sensitive to outliers. It can be normalized with the standard deviation of the observations from the reference instrument.

Response matrix	D_{matrix}	$\frac{\sum_1^N R_{s,matrix} - R_{s,filterd} }{N}$	gives the variability of the sensors
Factor of exceedance	FOEX	$100 * \left[\frac{N(M_i > RM_i)}{N_{total}} - \frac{1}{2} \right]$	Measures the over or underestimation of studied measurements against reference data. The best condition would be that FOEX = 0; unless, ideally, all measurements are equal to reference measurements; thus FOEX would be equal to 50. The same FOEX value (50) results from the complete underestimation of measurements, while FOEX = 50 in the case of a complete overestimation.
Interferant quantity	$Y_{int,z}$	$Y_z - Y$	the determination of the sensitivity coefficient
Normalized mean-square error	NMSE	$\frac{\sum_{i=1}^n (M_i - RM_i)^2}{\sum_{i=1}^n (M_i - \bar{M})^2}$	An estimator of the overall deviations between reference and sensor measurements; sensitive to extreme values.
The standard uncertainty of interferent	$\mu(int)$	$ \frac{Y_{int}}{C_{imax}} \cdot \sqrt{\frac{\sum (C_{imax}^2 + C_{1max}C_{1min} + C_{imin}^2)}{3}}$	standard uncertainty associated with the interferent
Temperature effect on Rs=X	$E_{T(Rs)}$	$\frac{n \sum_{i=1}^n X_i C_i - \sum_{i=1}^n X_i \sum_{i=1}^n C_i}{n \sum_{i=1}^n (X_i)^2 - (\sum_{i=1}^n X_i)^2}$	sensitivity coefficient for the measurement influencing variable
Sum of the square of the relative residuals	RSS	$\sum \left(\frac{x}{a - bx_i} - 1 \right)^2$	the sum of the relative residuals resulting from the orthogonal regression of the sensor values versus reference measurements
Mean bias error	MBE	$\bar{M} - \overline{RM}$	Estimation of the magnitude of differences between sensor estimation and reference values averaged over the whole sampling period.
Root-mean-square error	RMSE		Indicates the magnitude of the error and

$\sqrt{\frac{1}{n} \sum_{i=1}^n (M_i - RM_i)^2}$	retains the variable's unit; is sensitive to extreme values and outliers; tends to vary as a function of the standard deviation of the RM
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7.2. Statistical Calibration Evaluation

Orthogonal regression is used to assess the performance of each calibration method at individual air pollutant levels of the estimated outputs against reference data [149-153]. This relative expanded uncertainty U_r is compared with the data quality objectives (DQO) for the indicative method that is set by the respective directive body.

$$U_r(\gamma_i) = \frac{\left(2\sqrt{\frac{RSS}{(n-2)}} - u^2(x_i) + [b_0 + (b_1 - 1)x_i]^2\right)}{\gamma_i} \tag{1}$$

$U_r(\gamma_i)$ is the calibration estimation method of the uncertainty, which corresponds to the relative expanded uncertainty in measurements.

$$RSS = \sum_{i=1}^{\infty} (\gamma_i - b_0 - b_1 x_i)^2 \tag{2}$$

RSS is measured as the sum of the square of residuals.

7.2. AQ ML Models Evaluation for Low-Cost Sensors

In 2020, more than twenty machine learning methods and techniques were developed [154-159]. From recent works the most commonly applied techniques on AQ are 5 and given as a) Multiple Linear Regression (MLR), b) Online-Sequential Multiple Linear Regression (OS-MLR), c) Multi-layer Perceptron Neural Network (MLP NN), d) Extreme Learning Machine (ELM), e) Online-Sequential Extreme Learning Machine (OS-ELM). Each technique can deliver better results compared to the others depending on the nature of data [160-163]. There are 21 AQ ML evaluation parameters or key performance indicators (KPIs) from works [164-181] and are given as: i) Accuracy (AC); ii) Pearson Correlation Coefficient (CPCC); iii) Mean Absolute Error (MAE); vi) Median Absolute Deviation (MAD); v) Root Mean Square Error (ERMS); vi) Model Skill Score (MSS); vii) Training time (MTt); viii) Confusion Matrix (CM); ix) Gain and Lift Charts (CGL); x) Kolmogorov Smirnov Chart (CKS-); xi) Logarithmic Loss (Llog); xii) Gini Coefficient (GCo); xiii) Concordant – Discordant Ratio (RCD); xiv) Precision of Model (PM); xv) Recall (RM); xvi) Specificity (SM); xvii) F1 score (SF1); xviii) Precision-Recall or PR curve (CPR); xix) Chi-Square; xx) ROC (Receiver Operating Characteristics) curve (CROC); and xxi) PR vs ROC curve (CPR/ROC). The common binary terms used in ML are; True positives (TP): Predicted positive and are actually positive, False positives (FP): Predicted positive and are actually negative, True negatives (TN): Predicted negative and are actually negative, and False negatives (FN): Predicted negative and are actually positive.

Table 1. Multi-parametric Sensing Evaluation Parameters.

Parameters	Symbols	Mathematical/Graphical	Characteristics/Role
Accuracy	A_c	$\frac{TP + TN}{TP + FP + TN + FN}$	The most commonly used metric to judge a model.

Pearson Correlation Coefficient	C_{PCC}	$\frac{n \sum xy - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2]}}$ $* \frac{1}{\sqrt{[n \sum y^2 - (\sum y)^2]}}$	the measure of the strength of the association between the two variables.									
Median Absolute Deviation	MAD	$\frac{\sum x - \mu }{N}$	the measure of the variability of a univariate sample of quantitative data.									
Root Mean Square Error	E_{RMS}	$\sqrt{\frac{\sum_{i=1}^N (Predicted_i - Actual_i)^2}{N}}$	the differences between the values predicted by a model and the values observed.									
Model Skill Score	M_{SS}	$\frac{-\mu_M^2 - \mu_{RM}^2}{2a}$	skill score has a range of $-\infty$ to +1. A positive value of the skill score means the forecast is an improvement over the standard forecast.									
Confusion Matrix	C_M	<table><tr><th></th><th>Class 1 Predicted</th><th>Class 2 Predicted</th></tr><tr><th>Class 1 Actual</th><td>TP</td><td>FN</td></tr><tr><th>Class 2 Actual</th><td>FP</td><td>TN</td></tr></table>		Class 1 Predicted	Class 2 Predicted	Class 1 Actual	TP	FN	Class 2 Actual	FP	TN	also known as Error matrix and is represented by a table that describes the performance of a classification model on a set of test data in machine learning.
	Class 1 Predicted	Class 2 Predicted										
Class 1 Actual	TP	FN										
Class 2 Actual	FP	TN										
Gain and Lift Charts	C_{GL}		to check the rank ordering of the probabilities.									
Kolmogorov Smirnov Chart	C_{KS}		K-S is a measure of the degree of separation between positive and negative distributions.									
Logarithmic Loss	L_{log}	$\frac{-1}{N} \sum_{i=1}^N \sum_{j=1}^M (x_{ij} * \log(p_{ij}))$	log loss takes “certainty” of classification into account									
Gini Coefficient	G_{Co}	$G_{ini} = 2 * AUC - 1$	The coefficient ranges from 0 to 1 where 0 represents perfect equality and 1 represents perfect inequality.									
Precision of Model	P_M	$\frac{TP}{TP + FP}$	how much the model is right when it says it is right.									
Recall	R_M	$\frac{TP}{TP + FN}$	how much extra right ones, the model missed when it showed the right ones.									

Specificity	S_M	$\frac{TN}{TN + FP}$	a measure to see how separate the classes are unique.
F1 score	S_{F1}	$\frac{2 * precision * recall}{precision + recall}$	the harmonic mean of precision and recall. The high score is better.
Chi-Square	$M_{Chi-Square}$	$\sum_{i=1}^{\infty} \left(\frac{O_i - E_i}{E_i} \right)^2$	analyze the categorical data and evaluate tests of independence when using a bivariate table.
ROC Curve	C_{ROC}	$TPR(T)/FPR(T)$	T is the threshold parameter
PR vs ROC curve	$C_{PR/ROC}$	P_M/C_{ROC}	For detection of TNs

The type of application, nature of data, and abstract statistical analysis is the core factor in decision making for the productivity of KPIs in AQ.

8. Conclusions

The key challenges low-cost sensors utilization in the study of air quality measurement, assessment, systems, and their life-cycle were elaborated in this work in a systematic portrait with state-of-the-art contributions by researchers around the world. This research served its purpose in key factors and criterion in AQ a) the effective assessment techniques at urban and regional level defined the credibility and accuracy of air quality status; b) the appropriate sensors selection and optimizable components contributed to achieve the desired measurements; c) the tactical and strategic orientation of sensors assemblies and arrays were used to meet critical application challenges; d) the state-of-the-art sensors on chip options assisted in meeting the cutting edge market needs; f) the fabrication technologies and methods streamlined the properties, specifications and capabilities of sensors; g) the gradual improvement in testing methods of AQ sensors harnessed enhanced calibration methods; h) the multi-parametric and dedicated sensor testing and calibration systems gave better insights of operational, measurement, and transient anomalies; i) the usage of abstract key performance indicators in evaluation of sensing and calibration was swift and smart approach; j) the application of machine learning based signal processing techniques and approaches was state-of-the-art evaluation method that served as a horizon in accuracy and credibility of air quality measurements; k) the selection of appropriate key performance indicators assisted in the quality of air quality measurements; q) the usage of higher number of key performance indicators increased the trust factors in credibility of air quality assessment outcomes..

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