A Survey on Sensor Calibration in Air Pollution Monitoring Deployments

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***Abstract*—Air pollution is a major concern for public health and urban environments. Conventional air pollution monitoring systems install a few highly accurate, expensive stations at representative locations. Their sparse coverage and low spatial resolution are insufficient to quantify urban air pollution and its impacts on human health and environment. Advances in low-cost portable air pollution sensors have enabled air pollution monitoring deployments at scale to measure air pollution at high spatiotemporal resolution. However, it is challenging to ensure the accuracy of these low-cost sensor deployments because the sensors are more error-prone than high-end sensing infrastructures and they are often deployed in harsh environments. Sensor calibration has proven to be effective to improve the data quality of low-cost sensors and maintain the reliability of long-term, distributed sensor deployments. In this paper, we review the state-of-the-art low-cost air pollution sensors, identify their major error sources, and comprehensively survey calibration models as well as network recalibration strategies suited for different sensor deployments. We also discuss limitations of exiting methods and conclude with open issues for future sensor calibration research.**

***Index Terms*—Air pollution sensors, air quality sensor networks, low cost sensors and devices, sensor calibration.**

I. Introduction

URBAN air pollution affects the quality of life and public health. Pollutants such as particulate matter (PM), ozone (O_3), carbon monoxide (CO), or nitrogen dioxide (NO_2) can cause respiratory illnesses or cardiovascular diseases. A study by the World Health Organization estimated that 11.6% of all global deaths in 2012 can be traced back to air pollution [1]. Heavily polluted air also leads to environmental problems such as acid rain, stratospheric ozone depletion, and global climate change. Monitoring air pollution is of growing importance to increase public awareness and involvement in human health and sustainable urban environments [2].

Traditionally, air pollutants are monitored by fixed sites with expensive high-end sensing infrastructure run by governmental authorities. These monitoring sites are usually distributed sparsely and only suffice to estimate the average pollution affecting large populations. However, air pollution is known to be a complex phenomenon with sophisticated spatial and short-term variations [3]. For instance, in major streets, the pollutant concentrations may vary within tens of meters and over time within minutes [4]. Therefore, it is desirable to increase the spatiotemporal resolution of available air pollution information for the public to assess their personal health risks and take precaution measures.

A driving factor that enables these increased monitoring efforts is the availability of low-cost portable air pollution sensors. These sensors are usually small, consume low power, cost roughly between \$10 and \$1000 and are able to measure the concentrations of all the major air pollutants. Compared to bulky high-end solutions ($\geq$ \$10 000), low-cost sensors are particularly convenient for large-scale static and mobile deployments [5]–[8]. By now, low-cost air pollution sensors have been successfully integrated into various long-term deployments to provide fine-grained air pollution information for quantitative studies and public services [9].

Unfortunately the data provided by these deployments is often lacking sufficient accuracy [9], [10]. Many researchers report about serious inaccuracies when comparing the low-cost sensor measurements to reliable and accurate measurement of conventional monitoring sites [11], [12]. The reason for this unsatisfying performance can be linked to various limitations of state-of-the-art low-cost sensors, such as low signal-to-noise ratios or interference from environmental factors [13], [14].

In order to improve the data quality of existing and future air quality monitoring deployments, active research efforts are devoted to counteract these limitations with appropriate *sensor calibration*. By calibrating a low-cost sensor its measurements are transformed in a way that the calibrated measurements are able to closely agree with reference measurements from a high-end device. Sensor calibration is indispensable both before and after the deployments of low-cost air pollution sensors. Predeployment calibration is crucial to identify the primary error sources, select and train calibration models for low-cost sensors to properly function in the target deployment. Periodic post-deployment calibration is necessary to maintain consistency among distributed sensors and ensure data quality of long-term deployments.

Although calibration for air pollution sensors dates back to decades ago [15], [16], it has attracted increasing research interest because: 1) newly available air pollution sensors push the boundaries in terms of power consumption and portability while neglecting sensing accuracy and 2) air pollution sensors are deployed in new scenarios such as in crowdsourced urban sensing [17] and personal sensing [18], [19].

Related Surveys: Several surveys discuss low-cost air pollution sensor solutions and their different applications in

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real-world deployments. Rai *et al.* [5] summarized existing low-cost air pollution sensor technologies and divide them into two groups: 1) PM and 2) gaseous sensors. This survey provides an overview of existing testing and evaluation reports that highlight various important characteristics and limitations of state-of-the-art sensors. Similar articles focus on sensors for particular pollutants, e.g., Spinelle *et al.* [7] on volatile organic compounds (VOC) and benzene measurements, Jovaševic-Stojanović *et al.* [6] on PM and Baron and Saffell [8] on electrochemical (EC) sensors for gaseous pollutants. Yi *et al.* [9] reviewed the existing applications of low-cost air pollution sensors in static, vehicle, and community-based sensor networks. Thompson [17] provides an in-depth review of crowdsourced air pollution monitoring and their current demands and requirements for future successful deployments.

Our Contribution: While the related survey articles generally highlight the low accuracy of low-cost sensors, there is a lack of a comprehensive review of the reasons for the low data quality and calibration methods to improve it. In this paper, we summarize the existing scientific literature and give an in-depth list of different limitations of state-of-the-art low-cost sensors. The majority of this survey is devoted to different calibration models that have been proven successful in tackling the limitations and improving the data quality of low-cost air pollution sensors, and effective methods to recalibrate large-scale air pollution monitoring deployments. The discussed works stem from different research communities including atmospheric chemistry, measurement technology, and sensor networks. Thus, this survey provides a global picture of the diverse scientific results.

Roadmap: In Section II, we describe the most prominent sensing principles used in low-cost sensors. Further, we describe six common limitations that lead to generally inaccurate measurements. In Section III, we present three calibration models that are used to counteract different limitations that pose a challenge in any sensor deployment. In Section IV, we specifically focus on methods that maintain high data quality in long-term deployments. These network calibration methods are tailored to recalibrate the models presented in Section III in real-world deployments where access to highly accurate reference measurements is scarce. Finally, we conclude this survey in Section V and discuss multiple possible future work directions.

II. Air Pollution Sensors

Fast advances in technology and strong commercialization efforts are main drivers for an increasing number of low-cost sensors available nowadays [20]. Compared to high-end monitoring systems low-cost sensors typically require significantly less power and smaller packaging. Although these properties make low-cost sensors favorable for various large-scale monitoring applications, a diverse list of limitations hinders them to achieve a similar level of data quality as more sophisticated sensors. This section reviews the sensing technologies of low-cost air pollution sensors, summarizes their most common error sources, and points out the calibration opportunities to improve their measurement accuracy.

A. Sensor Types and Sensing Principles

As highlighted in [5] and [9], common low-cost sensors can roughly be divided in two groups defined by their target pollutant, i.e., PM (Section II-A1) and gases (Section II-A2).

1) Particulate Matter Sensors: PM describes a mixture of solid and fluid particles, which are typically classified by their size in diameter. PM_{10} describes the mass concentration of particles with a diameter smaller than 10 μm, $PM_{2.5}$ smaller than 2.5 μm. Ultrafine particles are nano-particles with diameters usually below 0.1 μm. These particles are known to cause serious effects on environment and human health and, thus, monitoring their concentration, size distribution, and composition is of high importance [2].

Low-cost PM sensors are almost exclusively based on optical sensing principles. The most prominent principle is based on light scattering, where air is pumped into a small chamber. Inside the chamber a light source, either an LED or a low-power laser, is illuminating the air. Depending on the number of particles in the air mixture, the light is scattered with different intensity, which can be measured by a photodiode. Certain low-cost PM sensors apply more sophisticated optical principles to also differentiate sizes of particles.

2) Gas Sensors: The most relevant gaseous pollutants in outdoor air with serious negative effects on human beings, animals, and the environment are sulphur dioxide (SO_2), oxides of nitrogen (NO, NO_2, $NO_x = NO + NO_2$), CO, and O_3 [2]. In indoor air mainly carbon dioxide (CO_2), VOC, and in some cases also CO are known to be possibly present in harmful concentrations [21].

The majority of commercially available low-cost gas sensors is therefore targeting to measure the concentration of one of these gases. With the exception of CO_2, which is either directly measured with light scattering sensors [20] or approximated by the presence of VOCs [22], the most popular sensing principles are based on EC or metal oxide layer reactions.

1) *Electrochemical:* An EC sensor consists in its simplest form of two electrodes: a) a working electrode and b) a counter electrode. Gases are either oxidized or reduced at the working electrode, which results in electronic charges generated. The generated potential difference at the two electrodes allows a current flow. This current is usually linearly proportional to the gas concentration. More advanced EC sensors incorporate one or two additional electrodes to improve stability and sensitivity [23], [24].
2) *Metal Oxide:* Metal oxide sensors (MOXs) use a sensing layer, where gases are either absorbed or desorbed. This reaction causes a change in conductivity of the material. In order to increase sensitivity the sensing layer needs to be heated to temperatures of at least 250 °C. State-of-the-art metal oxide sensors are capable of measuring all the major gaseous pollutants [25].

Based on the above sensing principles, manufacturers produce low-cost sensors and offer different features. Some sensors solely output an analog signal while others offer on-device signal processing, e.g., digitization of the analog signals or internal calibration. In the remainder of this survey

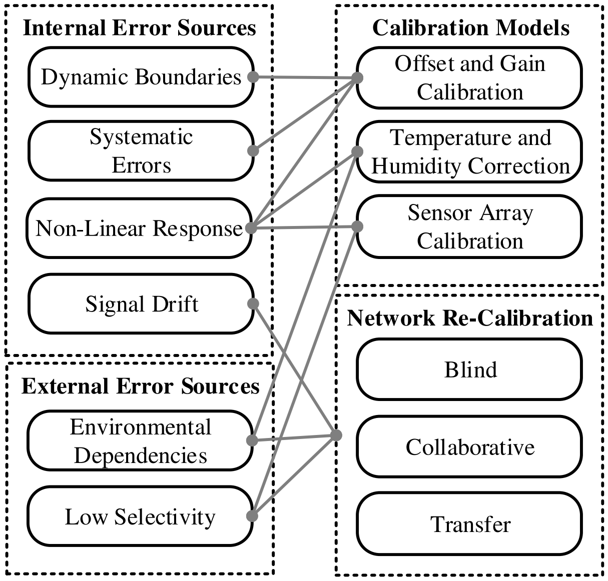

Fig. 1. Overview of typical low-cost error sources and their corresponding calibration approaches indicated by gray lines.

we do not differentiate between these different features. We regard a low-cost air pollution sensor as a black box with a signal output. The sensor is applied out-of-the-box and its output is used for comparison and calibration with references. This is the general approach done in the studies presented in this survey.

B. Error Sources

One of the most essential questions regarding the aforementioned low-cost sensors is how their measurements perform in comparison to high-quality references. An ideal sensor fully agrees with its corresponding reference sensor, i.e., exhibits a perfect linear relationship, as illustrated in Fig. 2(a). Unfortunately, the main reason why low-cost sensors have not yet been established as a trust-worthy air pollution monitoring fashion is their generally poor measurement accuracy [11]–[14]. In an exhaustive test report by Jiao *et al.* [12] perform a black box testing approach for multiple sensors. Out of 38 tested sensors only 17 correlate well to their corresponding reference sensors. Through exhaustive sensor testing schemes and signal analysis researchers were able to detect multiple different error sources of state-of-the-art low-cost sensors. As a result, most low-cost sensors significantly deviate from an ideal sensor (Fig. 2).

We divide the error sources in two groups, *internal* and *external* error sources, also summarized in Fig. 1. Note that we do not include error sources that have not yet been thoroughly tackled by calibration methods, such as slow response time or sensor mobility effects [26], [27].

1) Internal Error Sources: Internal error sources are generally known error sources and typically related to the working principle of low-cost sensors.

- *Dynamic Boundaries:* Dynamic boundaries define the range of a pollutant concentration in which a sensor is sensitive to. Especially the lower boundary, the limit of detection (LOD) [28], is important. Below this boundary the noise of a sensor signal starts to dominate and it becomes impossible to differentiate between concentration levels. Low-cost sensors often have an LOD that is close to the range of interest or even surpasses it. As a result, measurements at low pollution concentration are subject to high noise. An example of a low-cost sensor affected by high noise at low concentration due to imperfect dynamic boundaries is depicted in Fig. 2(b). Especially PM [5] and EC sensors [29] are known to be significantly affected by low signal-to-noise ratios at low concentrations. It is important that calibration procedures are applied with respect to this limitations.
- *Systematic Errors:* Systematic errors are of nonrandom nature and typically either characterized by a constant offset over the whole range of concentrations or an under- or overestimation of the concentration in certain ranges [11], [13], [14]. An example of a sensor response with a constant offset is illustrated in Fig. 2(c). They can often be attributed to imperfect calibration parameters and are generally not related to the sensing principle. Popular examples where systematic errors pose a challenge are factory calibrated sensors, as elaborated in detail in Section III.
- *Nonlinear Response:* Due to the nature of certain low-cost sensing techniques nonlinear relationships between a sensors and a references response are unavoidable. Nonlinear behavior is known to be an issue particularly for a wide range of PM sensors [30], [31] and metal oxide sensors [32]. Often sensor manufacturers already linearize the sensor response, e.g., by internal signal processing, or provide information about typical nonlinear behavior in the datasheet. However, additional factors such as environmental conditions are known to cause nonlinear behavior as well [33]. Fig. 2(d) shows an example of a nonlinear sensor response. A linear relationship is in general favorable because it allows the use of simple calibration models.
- *Signal Drift:* Low-cost sensors generally cannot maintain a stable measurement performance over a long time [34]–[36]. This usually happens due to aging and impurity effects, and leads to a slow drift of the sensors sensitivity. Signal drift is one of the most common error sources and seriously impedes long-term deployments with low-cost sensors.

2) External Error Sources: External error sources are induced by the working conditions of a sensor, such as environmental factors, and therefore are heavily deployment dependent.

- *Environmental Dependencies:* Changing environmental conditions can cause problems that almost any low-cost sensor is facing. Various laboratory reports show that certain *physical* ambient properties, especially temperature and humidity conditions, can have a serious effect on a sensors response. For instance, increasing humidity is notably decreasing the sensitivity of metal oxide [24], EC [37], and PM sensors [38]. As a result, low-cost sensors usually perform significantly worse in

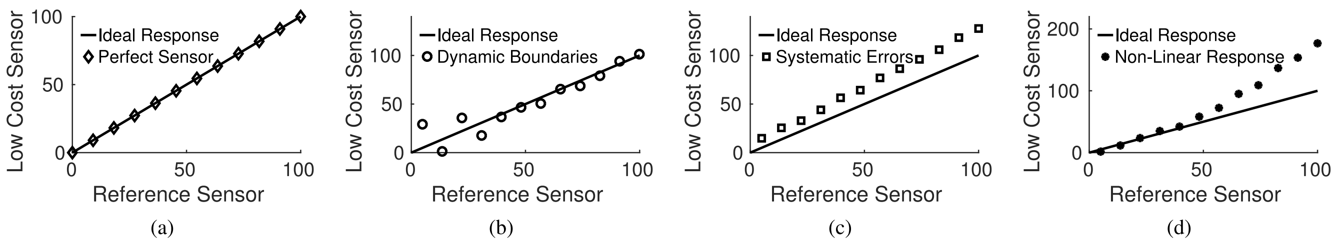

Fig. 2. Comparison of measurements (arbitrary unit) from a reference sensor (x-axis) versus measurements of different low-cost sensors (y-axis). (a) Response of a perfect low-cost sensor, (b) low-cost sensor affected by high noise at low concentration due to imperfect dynamic boundaries, (c) low-cost sensor suffering from systematically overestimated measurements, and (d) senor with a nonlinear response. The ideal response is a perfectly linear relationship between low-cost sensor and reference.

field deployments than in a laboratory setup. Further, environmental dependencies can also be responsible for nonlinear responses, e.g., for EC sensors [33].

- *Low Selectivity:* Typical metal oxide and EC sensors suffer from low selectivity. This means they are not exclusively sensitive to their intended target gas but are also cross-sensitive to, sometimes various, interfering substances in the air [39]. Especially in complex outdoor air these cross-sensitivities impose a fundamental challenge for low-cost gas sensors. PM sensors are usually not affected by cross-sensitivities because they are intended to detect a composition of different particles. However, in some cases where low-cost PM sensors are either used to detect particles from certain sources like car exhaust or to distinguish different particle sizes, cross-sensitivities are also considered as a fundamental error source [5]. Compared to environmental dependencies, the low selectivity problem is caused by purely *chemical* inferences and requires more sophisticated calibration efforts.

C. Sensor Deployments and Calibration Opportunities

A commonly used solution to reduce the errors of low-cost air pollution sensors is calibration. Calibration finds a relationship, i.e., a *calibration model* that maps the measurements of a low-cost sensor to those of an accurate reference sensor. Sensor calibration is performed both *before* and *after* the deployment of air pollution sensors to deal with different error sources (see Fig. 1).

1) Predeployment Calibration: The aim of predeployment calibration is to try to identify all possible internal and external error sources of a sensor in an observed and/or controlled environment before deploying the sensor in the field. Predeployment calibration usually assumes continuous availability of a high-quality reference sensor. One or multiple error sources listed in Fig. 1 can be detected by comparing the low-cost sensor to the reference sensor. These error sources are then tackled by developing a suited *calibration model* (Section III).

2) Post-Deployment Calibration: Post-deployment calibration is used for counteracting error sources that impede a consistent performance of a calibration model over time or in the actual deployment environment. These error sources are either heavily deployment dependent, such as harsh environmental conditions, or due to signal drift, which commonly occurs in long-term deployments. During post-deployment calibration, large numbers of sensors with irregular access to reference measurements need to be calibrated. This is achieved by applying the calibration models extracted from predeployment calibration to different *network recalibration strategies* (Section IV).

In Sections III and IV, we outline the existing calibration approaches, which are found in literature and used in low-cost air pollution sensor deployments.

III. Calibration Models

Calibration models are applied in both predeployment and post-deployment calibration. We start with the basic and fundamental model, i.e., offset and gain calibration, in Section III-A. Building on this basic model Section III-B presents a first extension that corrects for temperature and humidity effects. Finally, Section III-C summarizes an additional extension of the previous two models by also considering potential interference from other pollutants.

A calibration model takes the raw measurements of a low-cost sensor and transforms them to calibrated measurements, leveraging prior knowledge, e.g., datasheets or additional information, e.g., measurements from auxiliary sensors. Various mathematical methods can be applied and calibration models may vary for different types of sensors. Calibration parameters can be derived through measurements either in a laboratory setup (controlled environment) or in the field next to reference monitoring sites (observed environment). Table I provides a summary of available literature and different characteristics with respect to the three calibration models. We exclusively focus on calibration models that are either specifically tailored for air pollution sensors or general models that have been proven successful when applied to real-world air quality sensors.

A. Offset and Gain Calibration

Offset and gain calibration tackles calibration errors due to dynamic boundaries and systematic errors and removes potential nonlinear responses. It is one of the most essential calibration models that maps the raw sensing measurements to a target pollutant concentration.

1) Principles: Offset and gain calibration fits a calibration curve, either a linear or a nonlinear one, to model relationships

TABLE I
OVERVIEW OF SENSOR CALIBRATION MODELS PRESENTED IN THE LITERATURE

Calibration Model	Author	Method	Setup	Sensors
Offset and Gain Calibration	Castell *et al.* [11]	Ordinary Least Squares	Lab & Field	EC
	Spinelle *et al.* [13], [14]	Ordinary Least Squares	Field	EC, MOX
	Austin *et al.* [31]	Exponential Curve Fitting	Lab	LS
	Cheng *et al.* [40]	2^{nd} Order Curve Fitting	Lab	LS
	Carotta *et al.* [41]	Linear & Non-Linear Curve Fitting	Field	MOX
	Dacunto *et al.* [30]	Power Law Curve Fitting	Field	LS
	Balabin *et al.* [42]	Support Vector Regression	Lab	LS
Temperature and Humidity Correction	Holstius *et al.* [43]	Multiple Least Squares	Field	LS
	Piedrahita *et al.* [20]	Multiple Least Squares	Lab & Field	MOX, LS
	Jiao *et al.* [12]	Multiple Least Squares	Field	EC, MOX, LS
	Sun *et al.* [44]	Multiple Least Squares	Lab & Field	EC
	Martin *et al.* [45]	Multiple Least Squares	Lab	LS
	Eugster and Kling [46]	Multiple Least Squares	Field	MOX
	Barcelo-Ordinas *et al.* [47]	Multiple Least Squares	Field	MOX
	Hagan *et al.* [29]	Multiple Least Squares, kNN	Field	EC
	Wei *et al.* [48]	Linear & Non-Linear Curve Fitting	Lab & Field	EC
	Popoola *et al.* [33]	Linear & Exponential Curve Fitting	Lab & Field	EC
	Mead *et al.* [23]	Linear & Non-Linear Curve Fitting	Lab & Field	EC
	Gao *et al.* [49]	Higher Order Polynomial Fitting	Field	LS
	Masson *et al.* [32]	Non-Linear Curve Fitting	Lab & Field	MOX
	Tsujita *et al.* [50]	Non-Linear Curve Fitting	Lab & Field	MOX
	Sohn *et al.* [51]	Exponential Curve Fitting	Lab	MOX
Sensor Array Calibration	Pang *et al.* [37]	Multiple Least Squares	Lab & Field	EC
	Spinelle *et al.* [13], [14]	Multiple Least Squares	Field	EC, MOX
	Maag *et al.* [52]	Multiple Least Squares	Field	EC, MOX
	Fang *et al.* [53]	Multiple Least Squares	Field	MOX, LS
	Cross *et al.* [54]	Non-Linear Curve Fitting	Field	EC
	Zimmermann *et al.* [55]	Random Forests	Field	EC, LS
	Kamionka *et al.* [56]	Neural Networks	Lab	MOX
	Spinelle *et al.* [13], [14]	Neural Networks	Field	EC, MOX
	Barakeh *et al.* [57]	Neural Networks	Field	MOX
	De Vito *et al.* [58], [59]	Neural Networks	Field	MOX
	Esposito *et al.* [60], [61]	Neural Networks	Field	EC
	Esposito *et al.* [62]	Various machine learning methods	Field	EC
	De Vito *et al.* [63]	Various machine learning methods	Field	EC
	Lewis *et al.* [64]	Various machine learning methods	Lab & Field	EC, LS

Note: EC: Electrochemical, MOX: Metaloxide, LS: Light-Scattering (Particulate Matter and CO_2)

between raw sensor readings and pollutant concentrations. The calibration curve is defined by an offset term, i.e., the sensor's response to complete absence of the target pollutant, and a gain term that characterizes the sensor's response to increasing pollutant concentrations. Optimal offset and gain parameters capture the behavior of a sensor within its sensitivity range, i.e., the dynamic boundaries, and remove systematic errors attributed to poorly fitted calibration parameters.

2) Methods: The most popular methods to calculate offset and gain terms are ordinary least squares for a linear calibration line and nonlinear curve fitting, for instance with an exponential [31] or power law [30] gain term. Offset and gain calibration can be performed in both lab and field setups.

- *Lab Tests:* One way to acquire a calibration curve is to expose a sensor to various target pollutant concentrations in a controlled laboratory setup. Austin *et al.* [31] expose a low-cost PM sensor to different aerosol air mixtures in an air-tight enclosure. The gathered measurements are used to calculate a calibration curve defined by an offset and an exponential gain term. Castell *et al.* [11] followed a similar approach and calibrated different EC sensors by exposing them to five different gas mixing ratios. Their sensors show high correlation ($R^2 \geq 0.92$) and, thus, a simple linear calibration based on ordinary least squares was used to adapt the offset and gain terms. Similar laboratory calibration can be found in additional works [40], [42]. For certain commercially available low-cost sensors an initial laboratory calibration is already performed in the factory. Manufacturers usually follow similar approaches as found in the literature and either provide the sensors response over a range of target pollutant concentrations [65] or in the form of a calibration curve recorded in a laboratory setup [66].
- *Field Tests:* Various recent works propose to directly calibrate their sensors in an environment that is similar to the final deployment. The most prominent way is installing the sensors under test next to high-end sensors. For instance, Dacunto *et al.* [30] jointly deploy a low-cost $PM_{2.5}$ sensor with a high-end device in different indoor locations. In outdoor deployments the most prominent approach is to install the sensors under test directly next to governmental monitoring stations that often feature a variety of accurate pollution sensors. For instance, Fig. 3 shows a monitoring station of the governmental air quality monitoring network in Switzerland. Spinelle *et al.* [13], [14] deployed 17 different low-cost gas sensors next to high-quality sensors of a air quality monitoring station in a semi-rural area. Carotta *et al.* [41]

Fig. 3. Governmental monitoring station located in a suburban area in Switzerland.

deployed different MOX sensors next to a monitoring station located at a high traffic road and next to one in a low traffic intensive area. The highly accurate measurements from these monitoring stations are used to train and evaluate the calibration of the low-cost sensors.

3) Discussion: While laboratory setups are faster than field tests, many researchers [11], [20], [32], [41] recommend field tests for offset and gain calibration. In a laboratory setup, the environmental conditions during exposure are typically held constant, e.g., at room temperature and moderate relative humidity. Further, the chamber is usually filled with clean air mixed with the target pollutant concentration, i.e., without possible interference from other pollutants. In contrast, field tests allow that the sensors to be exposed to situations with realistic environmental conditions, e.g., changing meteorological parameters or interfering gases. Because the sensors are exposed to realistic pollution concentrations the parameters can be optimized to capture the behavior of the sensor within expected concentration ranges, i.e., with respect to the dynamic boundaries. For instance, Castell *et al.* [11] calculated an offset of their calibration curve around 1 ppb in a laboratory calibration and around 166 ppb in a field calibration for a CO sensor. By recalibrating the CO sensor, i.e., adapting its offset term, in the field they finally reduce the measurement error from 181 ppb by over a factor 2 to 87 ppb. Zimmermann *et al.* [55] showed similar results with four different sensors. Offset and gain calibration models calculated in a laboratory perform poorly in an outdoor deployment and are not in line with recalibrated models.

As explained in Section II-A2, errors of air pollution sensors can be environment-dependent. In part, *in-field* offset and gain calibration *implicitly* mitigates the impact of these external errors. However, environmental conditions are complex and subject to short- and long-term changes. As a result, simple offset and gain calibration achieves significantly worse results in field than in laboratory tests. For instance, Castell *et al.* [11] observed a drop of $R^2 = 0.99$ to 0.3 of a NO_2 sensor when moving from laboratory to field tests. To *explicitly* account for these environmental conditions temperature, relative humidity and interfering gases, advanced calibration models are needed, as we will describe in Sections III-B and III-C.

B. Temperature and Humidity Correction

Temperature and humidity correction augments air pollution measurements with concurrently measured temperature and humidity readings to calibrate the low-cost air pollution sensor.

1) Principles: The motivation of temperature and humidity correction stems from the influence of different temperature or relative humidity settings on sensors observed in laboratory tests. Pang *et al.* [37] observed a relative drop in sensitivity of roughly 20% for EC sensors when the relative humidity is increased from 15% to 85%. A similar observation is made by Wang *et al.* [24] for a metal oxide sensor. The sensor almost completely loses its sensitivity when changing from dry air to an extreme relative humidity of 95%. Wang *et al.* [38] demonstrated that increasing humidity can lead to an overestimation of the particle number of typical low-cost light scattering sensors. Similar sensitivity losses are also experienced under changing ambient temperature as summarized by Rai *et al.* [5]. These results make it evident that changing environmental conditions such as temperature and humidity need to be incorporated in the calibration process in order to improve the overall measurement accuracy of virtually any low-cost air pollution sensors.

2) Methods: Temperature and humidity correction is ubiquitous due to the availability of cheap and small but precise low-cost temperature and humidity sensors. Most works include these additional measurements in their calibration methods, and extend the single-variant mathematical models in offset and gain calibration (Section III-A) to the corresponding multivariant models.

A simple approach found in most of the investigation is to find the linear combination of raw air pollution, temperature and humidity sensor measurement that best captures the target reference concentration. The results in [12], [20], [29], and [43]–[46] all use multiple least squares to calculate this combination and show beneficial results for any type of low-cost sensor. Different approaches apply more complex methods to model the impact of temperature and humidity. Masson *et al.* [32] derived a detailed model that captures the physical effect of ambient temperature on their MOX sensor. Popoola *et al.* [33] developed a temperature baseline correction algorithm for EC sensors. They observe notable differences in temperature sensitivity for CO and nitrogen oxide (NO) sensors. While the CO sensor showed a linear relationship to its reference, the NO sensor exhibits a strong exponential relationship. Therefore, they model the reaction to temperature with a linear line fit for the CO sensor and a exponential curve fit for the NO sensor, which is used to correct the corresponding sensor signal. They are able to show a significant improvement for the NO sensor by improving the correlation from $R^2 = 0.02$ to $R^2 = 0.78$. Tsujita *et al.* [50] and Sohn *et al.* [51] similarly modeled the relationship of MOX sensors to humidity and temperature with exponential terms and compensate for them by fitting a calibration curve.

3) Discussion: The extensive list of different sensors that significantly improve their accuracy after temperature and humidity correction underline the severity of the problem. Temperature and humidity correction needs to be performed for any air pollution sensor regardless of its underlying sensing principles. In rare cases, the impact of ambient conditions can be precisely modeled using chemical process theory. This approach, however, requires deep knowledge of the underlying sensing principle, e.g., physical properties of the metal oxide sensing layer. Therefore, more simpler data driven methods dominate the different calibration methods. Due to the popularity of the problem recent low-cost sensors, especially fully digital sensor solutions, already integrate an internal temperature and humidity correction [66], [67]. However, the various field calibration works emphasize the benefit of directly compensate for temperature and humidity dependencies. Thus, it becomes evident that static correction schemes by manufacturers or laboratory calibration may be replaced by in-field calibration for optimal performance.

C. Sensor Array Calibration

Sensor array calibration is a generic extension of temperature and humidity correction that tackles another environmental dependent factor, interfering gases.

1) Principles: As described in Section III-A laboratory tests are usually performed by exposing the sensor to clean air that is mixed with the target pollutant. In most real-world deployments the air mixture is composed of multiple different components [23]. For instance, in outdoor and common indoor air multiple pollutants appear concurrently at diverse concentrations. These complex air mixtures particularly pose a substantial challenge for gaseous pollutant sensors. Instead of being selective to one single pollutant, low-cost sensors are typically sensitive to multiple pollutants at the same time with different intensities [24], [39]. This low-selectivity problem is also referred to as cross-sensitivities and, broadly put, equivalent to the temperature and humidity dependency, i.e., different factors in the environment are influencing a sensors response. Thus, the basic concept is the same as the temperature and humidity correction but often requires more complex methods.

By concurrently measuring all the cross-sensitivities it is possible to compensate for all interfering pollutants. This approach requires a sensor array, i.e., multiple different jointly deployed low-cost sensors. One option to create a sensor array is to install multiple sensors in a box to ensure common air sampling. Note that the majority of sensor arrays also include temperature and humidity sensors and, thus, in this case sensor array calibration is also performing a temperature and humidity correction.

2) Methods: Popular sensor array calibration methods can be divided in multiple least squares and neural networks.

- *Multiple Least Squares:* For certain cross-sensitivity problems a multiple least squares regression can be successfully used for calibration. One of the most popular examples is the cross-sensitivity of NO_x EC sensors on O_3 concentrations [52], and vice-versa [37]. Pang *et al.* [37] are compensating for potential influences of ambient NO and NO_2 concentrations on the signal of a O_3 EC sensor. The NO and NO_2 concentrations are, however, measured by a high-end sensing device. The effect of the two cross-sensitivities follow a linear behavior and, thus, a linear multiple least squares calibration can be successfully applied. Another investigation [52] follows a similar approach, but compensates for the cross-sensitivity to O_3 of a NO_2 EC sensor. The O_3 measurements are measured by another low-cost metal oxide sensor. It is shown that the measurement error of the cross-sensitive NO_2 sensor can be reduced by over 80% by simply incorporating measurements of an additional O_3 sensor in the calibration. Multiple least squares are effective to compensate for cross-sensitivities of 1) EC sensors to 2) the oxidizing gases NO_x and O_2.
- *Neural Networks:* In more complex cases, linear calibration models do generally not perform well [13], [14] and, therefore, different authors investigate the feasibility of nonlinear calibration models, mostly based on neural networks or related machine learning methods (see Table I). Spinelle *et al.* [13], [14] showed for a wide range of low-cost gas sensors an overall better performance of neural network-based sensor array calibration compared to multiple least squares and particularly to a offset and gain calibration based on ordinary least squares. For multiple O_3 and NO_2 sensors the coefficient of determination R^2 is improved from values below 0.3 to at least 0.85 and 0.55, respectively, using neural networks instead of linear models. They also show that for some sensors, in particular metal oxide CO and EC NO sensors, the cross-sensitivity limitation appears to be too severe and could not be solved by calibration with reasonable performance. Similar results are reported by Vito *et al.* [58], [59], [63], Esposito *et al.* [60]–[62], Lewis *et al.* [64], Barakeh *et al.* [57], and Zimmermann *et al.* [55]. Different types of machine learning techniques, with the majority being neural networks, are able to resolve cross-sensitivities of commercial low-cost sensors with the help of sensor array calibration.

3) Discussion: Compared to the other two calibration models, sensor array calibration is not a necessity for all sensors. The necessity of sensor array calibration mainly depends on the sensitivity profiles of low-cost sensors and the target pollutant. For instance, O_3 can in general be accurately measured with a single low-cost sensor due to the aggressive nature of ozone that in return simplifies the development of selective sensing principles. Other pollutants, for instance NO_x, are affected by the presence of aggressive interference factors and complicate the design of selective sensors. This two interacting factors pose a substantial challenge in choosing the optimal sensor array composition, i.e., what low-cost sensors are required to accurately measure the target pollutant. Therefore, various works [54], [55], [59] present a thorough analysis on which sensor array composition achieves the best performance in terms of measurement accuracy, precision, and stability. Such an analysis requires concurrent data of multiple different low-cost sensors that need to be tested on their feasibility in different sensor arrays. In some cases, the available low-cost sensors may not suffice for a successful array due to unresolved cross-sensitivities [13]. Thus, finding the optimal sensor array to tackle all cross-sensitivities remains an open problem. Further, similar to the two previous models authors agree that predeployment sensor array calibration needs to be performed in the field. The complex composition of pollutants in outdoor air requires the sensors under test to be exposed in their target deployment for a successful calibration.

D. *Comparisons of Calibration Models*

In summary, the most essential calibration model that is necessary for all types of sensors is a simple offset and gain calibration, i.e., mapping the raw sensor measurements to a pollutant concentration. Popular mathematical methods are linear regression or simple curve fitting possibly incorporating a nonlinear gain term. Due to the severity of the environmental dependency problem extending the basic model with a temperature and humidity correction becomes indispensable in order to significantly improve the measurement accuracy of any low-cost sensor. The correction can easily be done by concurrently measuring environmental parameters and include them in multivariable methods, such as multiple least squares or nonlinear curve fitting. Finally, additional environmental influences from interfering gases can be eliminated by incorporating sensor array calibration techniques. Cross-sensitivities are mostly problematic for EC and metal oxide sensors and heavily deployment dependent. Sensor array calibration requires concurrent measurements from different low-cost sensors and often sophisticated machine learning methods to capture the complex relationship between multiple cross-sensitive sensor and the target pollutant concentration. Overall sensor array calibration has been shown to produce most accurate data. Spinelle *et al.* [13], [14] evaluated the performance of the three different calibration steps with different gas sensors. For instance, the NO concentration measured by a calibrated sensor array achieves 15 and 41 times lower measurement errors compared to a single NO sensor with and without temperature correction, respectively. Similar results are shown by Zimmermann *et al.* [55]. Their sensor array calibration based on both linear and nonlinear methods achieves an almost one order of magnitude lower error than a simple laboratory offset and gain calibration for four different types of sensors.

The number of additional sensors and the amount of measurements needed to learn the model parameters increase with the complexity of calibration models. Compared to the other two calibration models, sensor array calibration also requires more training samples, i.e., covering a large range of different outdoor situations and, thus, is more time-consuming and complex to perform. Vito *et al.* [58] show a clear positive trend of accuracy and precision with increasing training data. Finally, they achieve a stable calibration with training data collected over 100 days. These long training epochs efforts are, however, justified in order to achieve high data accuracy during long-term deployments possibly spanning multiple years.

Note that a prerequisite to apply calibration models is the access to a highly accurate reference. A reference is usually available in lab or field tests before actual deployment of air pollution sensors. However, the sensors *after deployment* may have irregular access to a reference, which requires additional calibration strategies, as we will discuss in the next section.

IV. Network Calibration

Low-cost sensors are usually deployed in either a *static* or *mobile* sensor network for long-term air pollution monitoring. Even after predeployment calibration, these sensors need periodic recalibration due to sensor drift over time and changes in the target environments. Some works report a significant drift after already 1 month of deployment [35]. Thus, recalibrating sensors appears to be an absolute necessity in any long-term deployment.

An important commonality of post-deployment calibration is the lack of reference sensors to verify and potentially recalibrate low-cost sensors. This section reviews existing *network recalibration* methods, which calibrate a network of sensors with irregular or even no access to a highly accurate reference. We group the existing literature into three fundamental network calibration approaches, i.e., blind (Section IV-A), collaborative (Section IV-B) and transfer (Section IV-C) calibration, based on their assumptions or usage of virtual references. Table II holds a list of works that present network calibration methods specifically tailored for air quality sensors. Note that calibration in sensor networks is a general problem and, thus, some of the presented methods can also be directly applied or adapted to other type of sensor network applications consisting of temperature and relative humidity sensors [91], microphones [92], or barometers [93].

A. *Blind Calibration*

The concept of *blind calibration* [94] or *macro calibration*, is originally designed for general sensor networks and has also been applied to temperature and relative humidity sensor networks [91], [94]. The idea is to achieve a high similarity between measurements of all sensors in a network. A key assumption is that neighboring sensors measure almost identical values, or are at least correlated. This assumption is often not true for air pollution monitoring deployments. First, air pollution is known to be a highly complex system with large spatiotemporal gradients. Second, typical interdevice differences of low-cost air pollution sensors hinder equal measurements even in a dense small-scale network. As a result measurements of air pollution sensors in a large-scale deployment are in general neither identical nor necessarily correlated. A more practical assumption is to exploit situations in space and time where we can safely assume that all sensors within the given deployment measure the same pollution concentrations.

Tsujita *et al.* [50] installed a low-cost NO_2 sensor in the city of Tokyo, Japan. They recognize that the major error source of their sensor appears to be baseline drift of the calibration parameters over time. Because they continuously install their sensor at different locations where no accurate governmental stations are deployed, they propose an auto-calibration method. The sensor can be calibrated to reference stations that are not necessarily in their spatial vicinity when one can safely assume that the NO_2 concentration is almost

TABLE II
OVERVIEW OF NETWORK CALIBRATION METHODS

Approach	Author	Linearity	Mobility
Blind Calibration	Jiao *et al.* [12]	Linear	Static
	Fishbain *et al.* [68]	Linear	Static
	Moltchanov *et al.* [69]	Linear	Static
	Broday *et al.* [70]	Linear	Static
	Mueller *et al.* [35]	Linear	Static
	Pieri *et al.* [71]	Linear	Static
	Tsujita *et al.* [50]	Linear	Static
Mix: Blind & Collaborative Calibration	Dorffer *et al.* [72]–[74]	Linear & Non-Linear	Mobile
Collaborative Calibration	Xiang *et al.* [75]	Linear	Mobile
	Hasenfratz *et al.* [76]	Linear	Mobile
	Saukh *et al.* [77]	Linear	Mobile
	Saukh *et al.* [78]	Linear	Mobile
	Maag *et al.* [79]	Linear	Mobile
	Budde *et al.* [80]	Linear	Mobile
	Fu *et al.* [81]	Linear	Mobile
	Markert *et al.* [82]	Linear	Mobile
	Kizel *et al.* [34]	Linear	Mobile
	Arfire *et al.* [83]	Non-Linear	Mobile
Transfer Calibration	Cheng *et al.* [40]	Non-Linear	Static
	Zhang *et al.* [84]	Non-Linear	*not relevant*
	Zhang *et al.* [85]	Mix	*not relevant*
	Deshmukh *et al.* [86]	Mix	*not relevant*
	Fonollosa *et al.* [87]	Mix	*not relevant*
	Yan *et al.* [88], [89]	Linear	*not relevant*
	Bruins *et al.* [90]	MOX Heating	*not relevant*

identical at any point in the deployment region. To check these circumstances they use NO_2 measurements from four different monitoring stations and recalibrate the offset term of their low-cost sensor as soon as all four stations report a NO_2 concentration below 10 ppb. A similar method is also applied by Pieri and Michaelides [71]. A slightly adapted approach is presented by Moltchanov *et al.* [69]. Instead of assessing the possibility of a uniform concentration with reference measurements, they use specific time periods. In order to calibrate low-cost O_3 sensors they assume that the O_3 concentration is uniform during night time (01:00–04:00 A.M.), when local emissions of precursors, e.g., NO_2 traffic emissions, are negligible. During these time periods they calibrate six O_3 sensors to the reference measurements of one monitoring station. Because O_3 usually reaches concentrations close to zero during night, this approach again only allows for an offset recalibration. Finally, Mueller *et al.* [35] also divide their low-cost sensors in two groups, i.e., sensors that measures traffic related pollution variations deployed in inner city areas and background pollution sensors in outer city areas. This scenario is also illustrated in Fig. 4. They assume that at inner city locations O_3 and NO_2 concentrations are usually uniform during night and at outer city locations during the afternoon. Individual sensors installed in the inner city are then calibrated to a remote monitoring station in the inner city during nighttime and correspondingly for sensors located in the outer parts of the city in the afternoon.

B. Collaborative Calibration

Collaborative calibration extends blind calibration by creating virtual references where two mobile sensors meet in space and time such that they should measure the same physical phenomena. The basic idea of collaborative calibration is to exploit situations where two or more *mobile* sensors

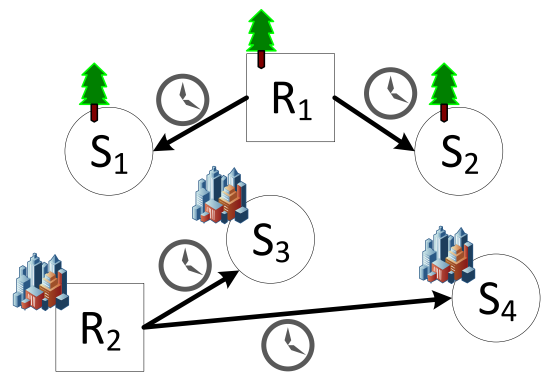

Fig. 4. Blind calibration scenario with rurally located sensors S_1, S_2, rural reference R_1, urban sensors S_3, S_4, and urban reference R_2. Sensors that are located in similar areas (rural or urban) are calibrated to references in similar areas during times when it is safe to assume that all sensor measurements are identical.

meet in space and time, i.e., referred to as sensor rendezvous. The notion of sensor rendezvous can also be found in other sensor network problems, such as energy efficient data collection [95] or sensor fault detection [77]. Further, collaborative calibration exploiting sensor rendezvous is also used in other sensor networks, e.g., crowdsensing applications using microphones [92] or barometers [93].

Sensor rendezvous can be utilized as references for calibrating mobile air pollution sensors. Sensors in a rendezvous are assumed to sense the same physical air and the range of a rendezvous can be empirically determined. For instance, Xiang *et al.* [75] defined a distance of at most 2 m between two sensors to constitute a rendezvous in an indoor air pollution monitoring deployment. Saukh *et al.* [78] showed that a distance of 50 m in urban outdoor deployments is a reasonable upper limit. Whenever a mobile low-cost sensor is in a sensor rendezvous with a highly accurate sensor, e.g., from a

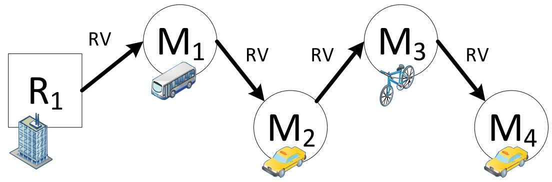

Fig. 5. Collaborative multihop calibration scenario exploiting sensor rendezvous (RV) between static reference R_1 and mobile sensors $M_{\{1,2,3,4\}}$. Whenever sensor M_1 is in the vicinity of the reference R_1 the low-cost sensor can be calibrated. In return, the freshly calibrated M_1 is calibrating M_2 during redenzvous, and so forth.

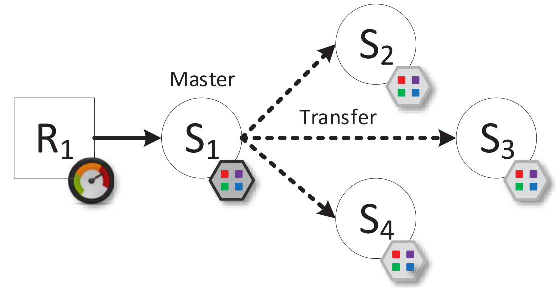

Fig. 6. Transfer calibration scenario between a reference sensor R_1 and sensors $S_{\{1,2,3,4\}}$. In a first step, sensors $S_{\{2,3,4\}}$ are standardized to a master sensor S_1 in order to achieve high similarity of raw measurements. In a second step, a calibration model acquired by the master S_1 with reference R_1 is transferred to all other sensors $S_{\{2,3,4\}}$.

governmental monitoring site, the low-cost sensor can use the reference measurement for calibration [78].

Arfire *et al.* [83] applied a nonlinear temperature correction for mobile EC sensors in a collaborative fashion with a reference sensor. Hasenfratz *et al.* [76] presented three different calibration methods based on weighted least squares that also incorporate the age of measurement at the time of the calibration parameter calculations. The methods in [76] are also applied by Budde *et al.* [80] to calibrate PM sensors in a participatory sensing scenario. These methods assume that a sensor is in rendezvous with one or more reference sensors multiple times under different conditions so that the sensor can collect a calibration dataset with high variance for calibration.

Unfortunately, not all sensors necessarily are in rendezvous with reference sensors frequently enough. As a consequence, some sensors in the network cannot be recalibrated. Therefore, some works additionally exploit rendezvous between a freshly calibrated and an uncalibrated low-cost sensor. In this case a sensor that has been freshly calibrated is used to calibrate an uncalibrated one, e.g., a sensor that has no rendezvous with references. In return, the second freshly calibrated sensor can also be used to calibrate others, and so on. Calibration is therefore performed in a chain-like fashion and, thus, this concept is also known as multihop calibration. A typical multihop calibration chain is illustrated in Fig. 5. Although multihop calibration allows to calibrate more sensors compared to calibration exclusively with references, it also poses multiple challenges. The most severe challenge is error accumulation over multiple hops, first reported by Hasenfratz *et al.* [76] and in detail evaluated by Saukh *et al.* [78] and Kizel *et al.* [34]. Due to the nature of least squares-based calibration models at every hop of the calibration chain calibration errors are accumulated. To counteract this error accumulation Saukh *et al.* [78] propose to use an alternative method, i.e., the geometric mean regression. It is not suffering from error accumulation, theoretically and practically proven, and is successfully used for offset and gain calibration of a real-world air pollution network. Maag *et al.* [79] presented a method that is tailored for sensor array calibration while also not suffering from error accumulation. Additional challenges of multihop challenges are tackled in [81] and [82]. Fu *et al.* [81] studied the effect of reference sensor placement on the performance of multihop calibration and present an algorithm to optimally design a practical deployment of static reference and mobile low-cost sensors. A privacy preserving multihop calibration scheme for participatory and crowd sensing deployments is introduced by Markert *et al.* [82].

C. Transfer Calibration

The third group of network calibration methods is known as transfer calibration. It has its origins mainly in industrial deployments using electronic noses (e-noses), i.e., metal oxide sensor arrays for hazardous odor detection. Although the related work mainly focus on e-nose calibration, transfer calibration can be applied to any sensor model. E-noses are typically calibrated by neural networks to detect multiple different odors or gases with one calibration model. Training such a neural network requires a lot of effort mainly due to training sample collection and model optimization. MOX sensor arrays do typically not produce identical responses compared to similar arrays, even coming from the same production batch [85], i.e., there are significant interdevice differences for e-noses. Therefore, each e-nose needs to be calibrated independently and mass production becomes an almost impossible task. Transfer calibration tackles this problem by applying a two-step calibration process. Assuming multiple e-noses, one e-nose acts as a master sensor. In a first step, all nonmaster e-noses standardize their raw sensor array signals individually to the raw ones of the master. This step is usually performed by linear regression methods, such as robust regression [86], ridge regression [89], direct standardization [87], or weighted least squares [85], and counteracts the interdevice differences. In a second step, the master node calibrates its response to the target gas or odor concentrations, e.g., by training a neural network calibration model [85], [86]. This model is now transferred to all nonmaster nodes, as illustrated in Fig. 6. Other popular methods used in the second step are support vector machines regression [87], [89] or classification-based methods to classify the presence of a certain gas using support vector machines [87], [89] or logistic regression [89]. Some works also combine the two steps using a global training framework, such as auto encoders by Zhang *et al.* [84] or a mixture of multitask and transfer learning by Yan and Zhang [88]. Bruins *et al.* [90] showed that the standardization in the first step can also be performed by applying an elaborate heating temperature control of the MOX sensor array.

TABLE III
DIRECT COMPARISON OF THE THREE NETWORK CALIBRATION METHODS

Method	Advantages	Disadvantages
Blind	+ Applicable to static and mobile sensors + Simple approach + All sensors in the network can be calibrated	- Only offset calibration possible
Collaborative	+ All calibration models possible + Sensor rendezvous assures high confidence in identical measurements of multiple sensors + Best suited for mobile air pollution monitoring deployments	- Only applicable to mobile sensors - Number of sensors that can be calibrated depends on sensor mobility - Non-linear calibration remains an open challenge in multi-hop calibration
Transfer	+ Applicable to static and mobile sensors + Non-linear calibration methods for all calibration models possible + All sensors in the network can be calibrated	- Limited performance - Only works with identical sensors - Little experience in real-world deployments

Since transfer learning only requires one complex calibration process for the master sensor array, it is clearly able to minimize calibration efforts in large-scale deployments. Unfortunately transfer learning approaches have mainly been evaluated in lab setups and not yet intensively in real-world deployments. One of the only transfer calibration adaptations using a real-world large-scale PM sensor deployment is presented by Cheng *et al.* [40]. In a first laboratory calibration step the PM sensors are standardized to a master sensor using second degree curve fitting. In the second step a neural network is used to perform a temperature and humidity correction. The neural network is constantly updated through out the deployment. Overall they achieve an increase in approximately 8% measurement accuracy compared to uncalibrated situations.

D. Comparisons of Network Recalibration Strategies

The three network calibration approaches all rely on different assumptions and fundamental design choices and, thus, also have different advantages. Table III compares the three methods and list their advantages and disadvantages. The least complex method based on blind calibration exploits time periods and locations of reference and low-cost sensors for calibration to assure that all sensors generate identical measurements. While this approach can be applied to any type of sensor in any deployment, the opportunities for calibration are generally sparse and, hence, only offset and gain calibration can be successfully performed. In order to increase the opportunities for calibration, collaborative calibration exploits meeting points or rendezvous between sensors. Consequently, collaborative calibration can only be applied to mobile sensor deployments. Depending on the mobility of the sensors it might not possible to calibrate all sensors within the network, e.g., a sensor with no rendezvous cannot be calibrated. So far it is unclear how collaborative calibration scales with the network size. This is not a substantial problem for the other two methods.

Finally, transfer calibration uses a two-step approach by first standardizing all deployed sensors to a master sensor and then transferring calibration parameters acquired by the master to all sensors. Transfer calibration has no restrictions on the possible calibration models or the mobility of sensor, with the exception of the static master sensor next to a reference. However, transfer calibration assumes that all sensors in the network: 1) drift in a equal way as the master node and 2) are equally affected by environmental conditions. These two assumptions are in general not true in typical air quality monitoring networks [85]. Therefore, up to now transfer calibration has not achieved satisfactory performance. Further, there is only little experience in real-world deployments.

Overall, all the methods have been proven to be successful in counteracting decreasing accuracy in their specific long-term deployments. In general the average measurement accuracy is increased after recalibrating a sensor network and, thus, the existing results point out the necessity of recalibration. However, the different strengths and weaknesses of the three methods presents the need for an universal network calibration method. Currently, there is no one-for-all network calibration solution available. Recent research efforts investigate the possibility of a general applicable network calibration method, e.g., by combining different aspects from the three methods. Some theoretical investigations already provide mixtures of different models. For instance, Dorffer *et al.* [72]–[74] combined the two ideas of blind and collaborative network calibration to increase the possibilities for sensor recalibration. A key benefit of enhancing and mixing different network calibration aspects will thus help to assure that all sensors in a network can be calibrated. We discuss a detailed possibility in Section V.

V. CONCLUSION

In this survey, we review the sensing principles and error sources of low-cost air pollution sensors, and the calibration models and recalibration strategies to improve the accuracy of these sensors before and after their deployments. Back to decades ago, air pollution information was accessible only at coarse spatiotemporal resolution. Advances in portable air pollution sensors have enabled fine-grained air pollution monitoring at low cost. Along with the convenience brought by low-cost sensors come with the challenges in ensure quality of their measurements. We demonstrate the effective calibration models and strategies suited to improve the accuracy of diverse air pollution sensors in various deployments. In the era of Internet of Things, where air pollution monitoring becomes more crowdsourced and personal, we also identify several largely open and attractive opportunities for future sensor calibration research.

A. Calibration Model Benchmarking

Popular ways to assess the performance of calibration models are metrics related to measurement error and correlation. A widely used metric is the root-mean-squared-error between the calibrated measurements and its reference counterpart. Equally popular is the coefficient of determination R^2, which captures the amount of variance of the reference measured is finally captured in the calibrated measurements. There exist a variety of other statistical measures used in related work. An open challenge in assessing the performance of calibration methods is a unified way to declare a limit of these metrics when the calibrated measurement suffices for a certain application. Some researchers already follow benchmarks proposed by official authorities, for instance, the data quality objective (DQO) presented by the European Parliament [7], [11], [14]. The DQO provides a clear metric that air quality sensors need to satisfy in order to be applied as official measurement provider. As expected calibrating low-cost sensors in order to fulfill these objectives is very challenging, but also not necessarily needed for quantitative applications such as personal exposure assessment. A possible future direction is to build a benchmarking framework that defines data quality guidelines for low-cost air quality sensor networks with respect to different pollutants and applications.

B. Context-Aware Network Recalibration

As presented in Section IV, all network recalibration schemes need to identify situations where it is safe to assume that multiple sensors measure the same or similar phenomenon. The recalibration opportunities are either based on coarse assumptions (in blind and transfer calibration) or mobility (in collaborative calibration). With the rise of big data and urban computing the relationship between a sensors context, e.g., detailed land-use data, and the expected pollution concentration can be precisely modeled and is deeply understood. By classifying sensor locations according to their land-use context, e.g., nearby traffic, elevation or population density, a number of confident and new recalibration opportunities can be increased. These context-based virtual recalibration opportunities will greatly improve the calibration ability of a sensor network and allow additional calibration models as well as mathematical methods.

C. Calibration With Little Overhead

Machine learning methods, such as neural networks, have become popular tools for sensor calibration in the last few years. Although they offer powerful capabilities of capturing complex and possibly nonlinear relationships between multiple sensors, they require large amounts of measurements to train an accurate calibration model via standard supervised learning. This can be a burden for model updating in network recalibration, especially for sensors that have limited reference samples. In addition, the number of samples available for calibration may vary for different sensors in a deployment. Consequently, the accuracy of calibration models can also differ for different sensors due to imbalanced training data. Some recent study [19] has exploited techniques such as semi-supervised learning to reduce the amounts of training data for sensor array calibration. However, it remains open how to reduce the training overhead of network recalibration and achieve consistent calibration accuracy for all sensors in a networked deployment.

D. Quantification of Trust

Due to limited access to reference data during a sensor network deployment not only recalibration is a challenging task but also the evaluation of the calibration performance. Control mechanisms to assess the trust of the calibrated measurements offer therefore additional future research directions. Metrics such as accuracy bounds for sensor measurements [96], discrete reputation scores [97], or internode sensor confidence [98] and correlation [77] can be applied in a network-wide trust model to provide a notion of quality of service of the air quality monitoring sensor network. Additionally, by observing a trust metric one can estimate the need for recalibrating certain sensors within the network or apply filtering methods to assure high data quality. Different related works [99] propose trust mechanisms in general networks, however, these have not yet been applied in the specific scenarios of air pollution monitoring networks.

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