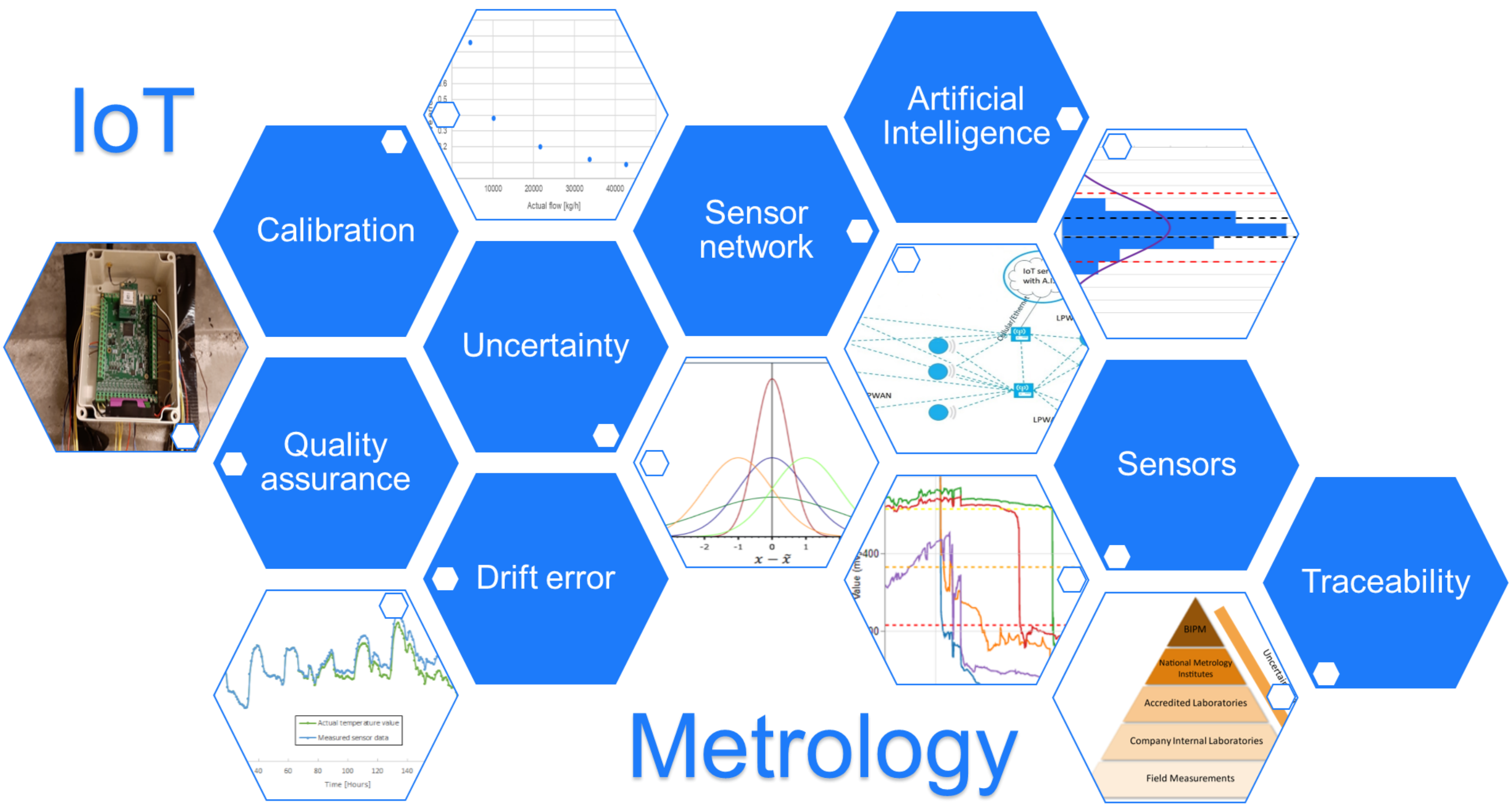
FORCE TECHNOLOGY

Guidelines on the Use of Metrology in IoT



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Abstract

IoT systems based either on a single device or on a network of multiple devices are becoming increasingly common in various industries. One major reason behind this fact is the increased availability of low-cost sensors. The quality of data measured by some IoT systems with low-cost sensors is typically either unknown or low. However, an IoT system might need a high quality of data, such as for quality assurance or due to legislation requirements. Therefore, there is a need to develop methods and best practices of how to ensure a certain level of measurement accuracy and data quality in the IoT applications. In this white paper, we highlight various tools that can be used in this context. The proposed toolbox covers different use cases and needs and is applicable in various stages of the lifetime of an IoT product, from the design to the operation phase. Our purpose is two-fold: First, to create awareness within the IoT system designers, managers, and users about the importance of having accurate measurements and some of the challenges that the IoT systems might have in this regard. Secondly, to help them decide which method and when is more appropriate for their application.

1. Why is Metrology Important in IoT?

Metrology, being the science of measurements, is vital to almost everything in the modern society. From the manufacturing of sophisticated technological equipment, such as mobile phones, to the monitoring of our environment, and analysis in healthcare.

Due to the high diversification of its applications, there are various reasons why metrology might be relevant for a company or industry. To better understand these reasons, FORCE Technology organized a webinar in March 2021 with over 100 participants from the industry or research organization worldwide. During the webinar the top answer to the question of "why is metrology required for your product?", with almost 27% of 44 respondents, was quality assurance. Runner ups are legislation with almost 18%, and customer requirements or "custody transfer/change of ownership" with almost 17%.

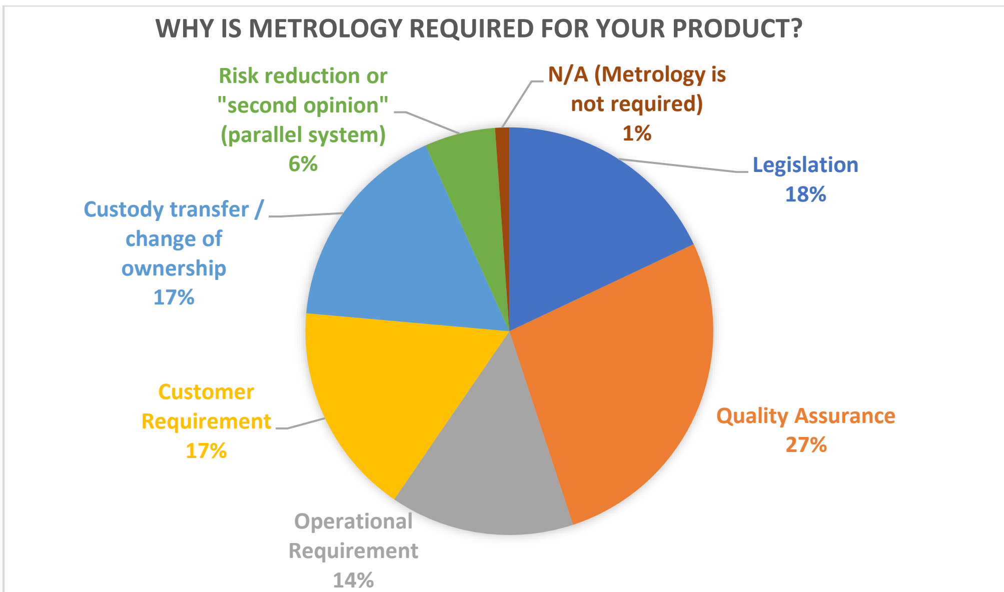


Figure 1: Answers from 44 respondents to the questions "Why is metrology required for your product?"

One of the most important reasons to use metrology, especially in manufacturing, is to ensure quality. This can be relevant either after production (**quality control**), in order to prove that the parts are conforming to the specifications, or during production, as to ensure that parts are being produced according to specification in the first place (**quality assurance**). As the American Society for Quality (ASQ) explains on their website [1], "the 'cost of quality' isn't the price of creating a quality product or service, it's the cost of NOT creating a quality product or service". Regardless of whether it is during the production process, when making decisions, or other areas within a company, utilizing metrology makes a major contribution to improve the productivity and optimizing the costs.

The accuracy of the measurements in some cases is more critical than in others. In healthcare and pharma market, for instance, making accurate measurements is of the utmost importance. If the medication dose given to a patient is not correct or if the measurements of vital signs of the patient are inaccurate, human lives may be at risk. In the same category belongs anything that might endanger the public health if measurements are not accurate enough, such as food safety and radiation measurements.

In applications like these there are usually regulations that must be followed and legal implications in case they are not. This is where metrology becomes important to ensure compliance to the laws. In this category of legislation reasons, we can also add the cases of “custody transfer/change of ownership”, which is typical in the gas and oil industry, but also the shipping sector. That is, if an asset changes ownership from one party to another, it is important to determine that asset accurately. Put in a bigger perspective, any commercial transaction that takes place, either business to business (e.g., gas consumption metering) or business to client (e.g., measurements of gasoline intake at the pump) involves measurements that must be accurate. Therefore, these trade cases are usually governed by certain legislation or at least contracts between the parties.

Moreover, customer requirements might demand the use of metrology as to manufacture quality parts, with tight tolerances and/or make accurate measurements. That can be either due to legislation/regulatory reasons or due to demands stemming from the industry (e.g., automotive or aviation). For instance, it may be required for a manufacturer of alcohol metering IoT devices to have a well-defined uncertainty for its devices, if its customers are measuring that the alcohol content in an alcoholic beverage is correct. Another example could be when IoT length measurement sensors are used for inspecting that the dimensions of axles produced in a factory are correct.

Metrology is also useful when novel applications and/or sensors emerge, as a way to relate the new measurement to an existing reference. Imagine a case where cameras are used to estimate the weight of livestock. In this non-conventional application, how can we translate the images taken by the camera to a weight measurement? For ordinary scales, there are standards that describe how to calibrate them, but as the scale is now replaced by AI the standards can no longer be applied as they assume that the scale is based on a plate with a weight on top of it. Therefore, the most logical way would be to create a database of concurrent weight measurements from a conventional weighing station and images from the camera. Then algorithms have to be developed to correlate the two datasets and create a decision mechanism, probably based on Machine Learning. Additionally, the accuracy of the algorithm and decision needs to be specified. Metrology is involved in all stages of this process.

Lastly, metrology might also be important when low-cost sensors are involved. In the recent years low-cost sensors have started being used more and more in IoT systems. For example, to measure Particulate Matter (PM) concentrations or gas pollutants in the atmosphere. In many cases these sensors compromise cost with measurement accuracy and/or less sturdiness against environmental conditions. Then, applying metrology could be useful in order to improve their precision and accuracy or better define it.

2. How Much Accuracy Do I Need?

It is not always easy to evaluate the level of accuracy needed for an IoT application. This is certainly a necessary step in the process of introducing metrology in an IoT device. However, the exact answer to the question will be different from case to case and each company needs to explore the sources of requirements that might be relevant to its specific case.

Sometimes the uncertainty is determined through the regulations and requirements for metrology. This is obviously the case when legislation is this reason. When some regulations or recommendations must be followed, it is apparent that the needed accuracy will be defined through them. For example, OIML R 140 is an international recommendation applied on measuring systems for gaseous fuel, published by the international organization of legal metrology. The recommendation states that measuring systems of accuracy class C must have a maximum permissible relative error of ± 2.0 %. Similar statements can be found in other standards and recommendations for applications that fall under the jurisdiction of legal metrology.

In the application area of custody transfer, such as for natural gas, there are usually contracts in place between the involved parties. These contracts state if the meters have an accuracy of more than X.XX%, the difference between this limit and the actual accuracy calculated during a calibration must be reimbursed from the one party to the other. Therefore, such agreements are another source of defining the application's accuracy.

Another example could be again the legislation that states that the level of CO_2 concentration in a classroom should be below 1000 ppm. If the measuring sensors used to verify this limit are inaccurate though, the limit must in fact be set lower than the 1000 ppm.

In regard to the calibration of the EMC (Electro Magnetic Compliance) chambers, the regulations say that the measurement uncertainty can be entirely omitted if it is found to be below ± 4 dB. If it is above this number, though, then the full uncertainty must be applied, hence lowering the limit.

Sometimes even, it might be almost impossible to define a specific number for the accuracy of the IoT system. Let's take the example of an IoT system with cameras that apply A.I. to estimate the weight of livestock as they grow. But if there are no historic data on the livestock's weight while they grow, how do we estimate how accurate our new IoT system needs to be? This case highlights that defining the required accuracy of an application might be challenging and the lack of an easy way to do it might eventually lead to higher investments in time and capital than initially estimated.

3. How to Apply Metrology in IoT?

This section gives recommendations and examples of specific tools and methods that can be applied in order to improve the accuracy of the measurements taken by IoT devices. They range from the classical traceable calibrations in an accredited lab to sensor validation techniques in the field.

Metrology can be used at any phase in the life cycle of an IoT device, from the design phase and manufacturing to the deployment and operation. Figure 2 illustrates what methods are relevant for each of these phases.

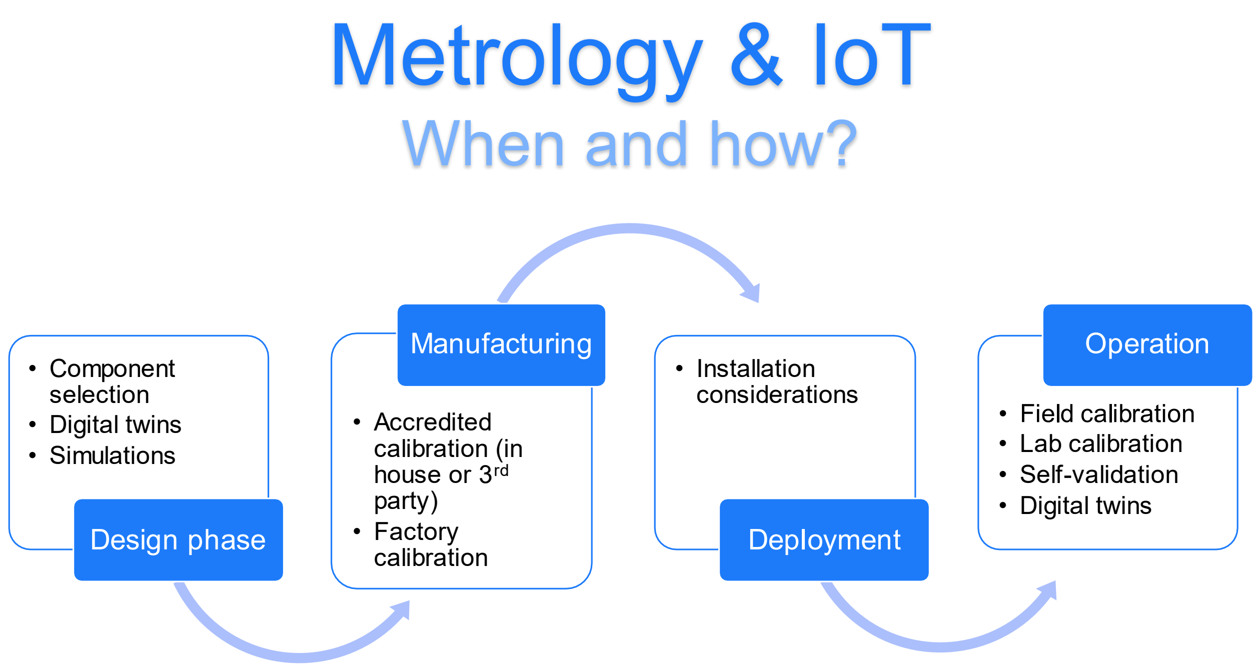


Figure 2: Diagram showing when in the life cycle of an IoT device (from the design phase to its operation) and how to apply metrology

3.1. Traceable Calibrations

One of the most obvious and reliable ways to bring metrology in the IoT devices is to apply the principle of metrological traceability from the classical science of metrology. Following these principles, all sensor devices are calibrated before being shipped to customers, in a process that relates their measurements to a stated reference (usually a national or international standard), through an unbroken chain of comparisons with stated uncertainties.

These calibrations are typically performed at an accredited third-party laboratory that is certified to perform such calibrations. In Denmark it is DANAK the provides such accreditations. The instruments or reference standards used for the calibrations by these laboratories are in-turn also calibrated by another calibration facility and have less uncertainty that the desired uncertainty of the sensor under test.

Usually, it is the National appointed Metrology Institute (NMI) of each country that is calibrating these instruments or references. (As for instance, in Denmark, DFM is 'NMI' for parameters such as gasses and particles, just like FORCE Technology is 'NMI' for parameters such as gas flow and humidity in air).

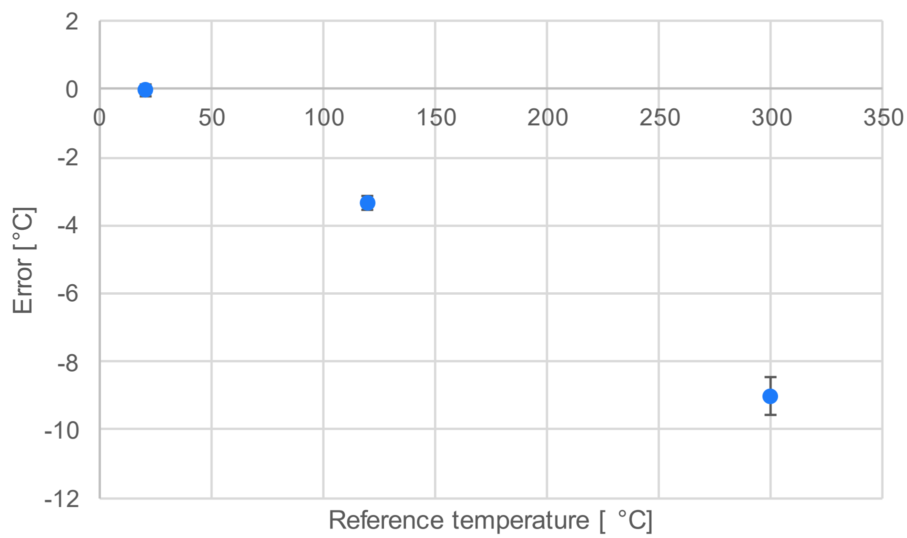


Figure 3: Example of a three-point calibration curve for a digital thermometer. The error values between the thermometer and a reference thermometer are reported at three reference temperatures, along with the calculated uncertainty for each value.

However, alternative models can also be followed. For example, an IoT device supplier could get accreditation for its own internal laboratory and employees. In that case he could calibrate its own devices internally, applying metrological traceability, without the need to use the services of a third party.

Another alternative for an IoT device supplier would be to apply the practices that are used in the industry with the process control instrumentation. As it is typical in this context, only a few process instruments are periodically sent to an accredited laboratory for calibration. These are then used within the production site or the entire company as reference standards (working standards) and all other process instruments are calibrated with these, but not necessarily using accredited procedures (e.g., according to ISO/IEC 17025). The IoT device manufacturer can similarly calibrate a few reference devices at a third-party accredited laboratory, and then use them to perform in-house factory calibration of all the other devices that are manufactured, in a similar way that Texas Instruments (TI) and Analog Devices (AD) does for their temperature sensors (TI: TMP117, AD: ADT7320), and Sensirion for their STS3x series temperature sensors.

The reader should however be aware that the uncertainty increases with every calibration and every device that gets calibrated cannot have an uncertainty better than the reference device. Therefore, the solution where a calibrated reference device is used to calibrate devices within the company, will most probably result in a higher uncertainty for the process devices since an extra calibration stage is involved.

Table 1 shows an example of an uncertainty budget for the calibration of a temperature block calibrator. The calibration is performed by comparing the temperature indication of the block, t_R, with the temperature, t_S, determined with a standard thermometer, which is traceable to national standards. As shown in the uncertainty budget, the standard thermometer uncertainty is only 0.013 °C and several other sources of correction and uncertainty are identified that contribute to the final measurement uncertainty being 0.276 °C.

Table 1: Example of an uncertainty budget for the calibration of a temperature block calibrator. Inspired by an example in [2]

Quantity x_i	**Source of uncertainty**	**Estimate (°C)**	**Coverage interval (°C)**	**Distribution**	**Divisor**	**Uncertainty contribution (°C)**
$t_R - t_S$		0.55				
δt_S	Standard thermometer uncertainty	0.00	0.03	normal	2	0.013
δt_i	Resolution of indicator	0.00	0.10	rectangular	$2\sqrt{3}$	0.035
δt_H	Hysteresis effects	0.00	0.05	rectangular	$2\sqrt{3}$	0.012
δt_B	Axial inhomogeneity	0.00	0.5	rectangular	$\sqrt{3}$	0.271
δt_L	Loading effects	0.00	0.05	rectangular	$\sqrt{3}$	0.024
δt_V	Stability in time	0.00	0.006	rectangular	$2\sqrt{3}$	0.019
δt		0.55				0.276

Various calibration features can be of importance in the context of IoT devices. When a manufacturer wants to scale up the production of devices that requires traceable calibration, then it is required to be able to calibrate the devices within short time period. With the current typical way that calibrations are performed, where only a single device is calibrated at a time, in a manual way and with only few parameters under calibration, the time required to calibrate a big number of devices is anything but short. Therefore, it is important to develop methods of calibrating multiple devices concurrently (bulk calibration), in an automated procedure with minimal manual intervention and a multi-exposure calibrating environment, where multiple parameters such as temperature and gases are controlled at the same time.

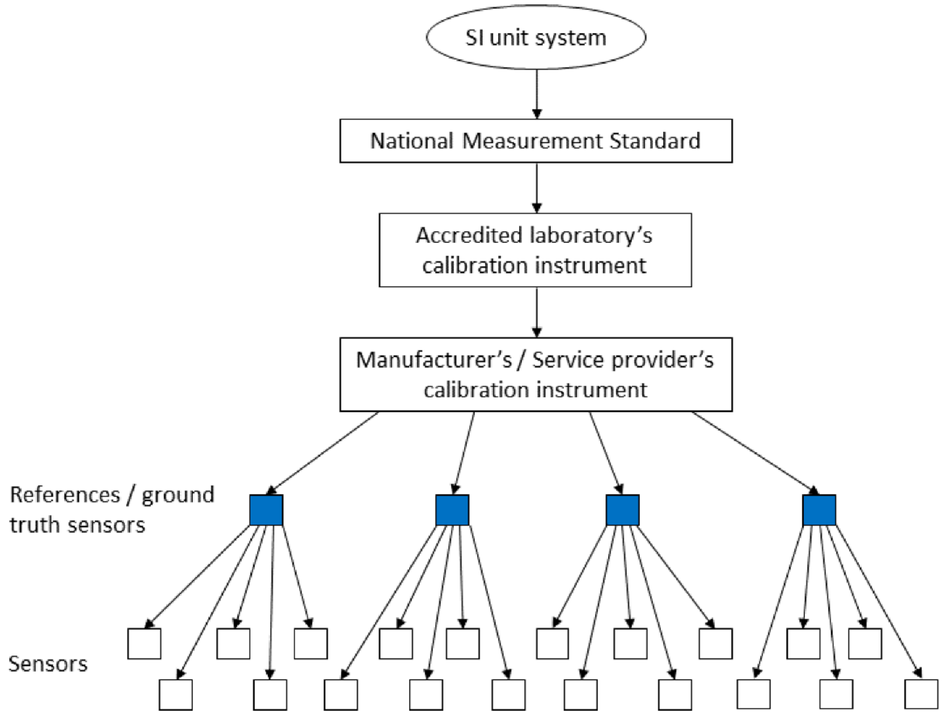


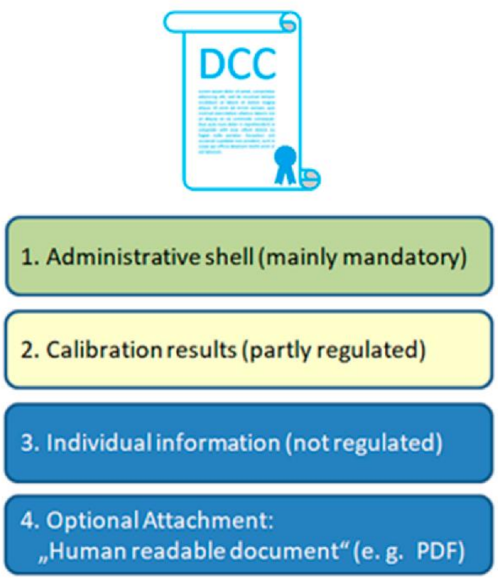
Figure 4: An example of how metrological traceability in an IoT sensor network can be achieved. Reproduced from [3] without modifications, licensed under CC BY 4.0.

3.2. Digital Calibration Certificates

Digital Calibration Certificates (DCCs) are being developed to replace paper calibration certificates. Because they are electronic files, they can be delivered instantly and securely to customers. Some calibration certificates have already moved to digital versions of the paper certificates in the form of pdf files which are digitally signed. But even though these are in digital format they are not the same as DCCs, since the pdfs are still just the regular certificates shown digitally. There is one important difference between those and DCCs, which is that DCCs are machine readable. Having a paper-based or pdf certificate means that the calibration information on the certificate must be manually transcribed into the processing system which uses the calibrated device/equipment. Because the DCC is machine readable, it eliminates this manual transcription and thus eliminates the possibility of human error during transcription [4].

The DCC was initially proposed by PTB, the National Metrology Institute of Germany, and is still being developed with the vision to replace paper-based certificates with a fully digital process leading to the DCC. The proposed file format of a DCC is XML as it can be read and interpreted by software. This concept is being further developed in the EMPIR project "SmartCom" which is funded by the EU Horizon 2020 program. Along with the development of the DCC, the SmartCom project has also developed an XML format for representing the measurement results. This is another important component of the DCC: the digitized version of the SI units known as D-SI. The D-SI embodies all information required for exchanging measurement results in a digital form. Furthermore, the components of the DCC developed through the SmartCom project are in full agreement with the ISO 17025 standard [4] [5].

The DCC of the SmartCom project consists of four parts. The first part is an administrative shell with mandatory information such as unique identifiers of calibrated device, the DCC, customer, and calibration lab. The second part is for the calibration results and relevant metadata like measurement equipment and calibration methods. It is partly regulated. The third section is for individual information and is not regulated. It contains information such as comments or figures and is not necessarily machine readable. The fourth part is an optional attachment. This would typically be for human-readable documents such as a copy of the calibration certificate in, for instance, a pdf format [3].



(a)

```xml
<dcc:quantity id="volume_cal_2">
  <dcc:name>
    <dcc:content lang="en">volume at t = 20 °C</dcc:content>
  </dcc:name>
  <si:real>
    <si:value>1.2480E-6</si:value>
    <si:unit>\metre\tothe{3}</si:unit>
    <si:expandedUnc>
      <si:uncertainty>0.0005E-6</si:uncertainty>
      <si:coverageFactor>2</si:coverageFactor>
      <si:coverageProbability>0.95</si:coverageProbability>
    </si:expandedUnc>
  </si:real>
  <dcc:influenceConditions>
    <dcc:influenceCondition>
      <dcc:name>
        <dcc:content lang="en">temperature</dcc:content>
      </dcc:name>
      <dcc:data>
        <dcc:quantity>
          <si:real>
            <si:value>20</si:value>
            <si:unit>\degreecelsius</si:unit>
          </si:real>
        </dcc:quantity>
      </dcc:data>
    </dcc:influenceCondition>
  </dcc:influenceConditions>
</dcc:quantity>
```

(b)

Figure 5: Example of the Digital Calibration Certificates (DCC) structure. High level syntax of the DCC with its four distinct parts (a), and an XML extract from a calibration result of a volume measurement, where the D-SI data model is also visible (si:real) (b). Reproduced from [3] without modifications, licensed under CC BY 4.0.

Since the vision of the DCC is a fully digital process, it requires a digital infrastructure to support it. There are two parts to this infrastructure. From the perspective of metrological institutes there is the process leading up to the creation of the DCC, which from that point of view can be regarded as the final stage [4]. But after the creation of the DCC the customer of the calibration service will need to import or implement it into its own system, which also needs to support it. Thus, the first part of this infrastructure is related to the calibration of the devices and the metrological traceability, and it ends with the creation of the DCC. While the second part of this infrastructure is related to the use of the DCC.

The value of the DCC is to document the accuracy of the IoT devices and to fill-in the gap of the lacking metrological traceability in IoT sensor network systems with self-calibration. Accuracy can of course be established through any kind of calibrations and with corresponding certificates, but what the DCC can offer, is to additionally make it a much more integrated part of an IoT system. For instance, it fits well with the trends of “Industry 4.0” and the metrological equivalent “Metrology 4.0”, where the aim of the latter is to have current non-digital processes reimplemented in a fully digital manner [4]. Not only does the DCC help improve the accuracy of IoT systems with a more integrated solution for accessing metrological data of the IoT devices, it also establishes the traceability of this accuracy. This is done through the unbroken chain of calibrations. This traceability is exactly one of the weak points of IoT device calibrations.

An important challenge of implementing DCCs in IoT systems is to determine where to store them. Based on the storage location, a few different scenarios have been identified. Scenario 1 is to store the DCC on IoT devices, where scenario 1a would be the sensor device storing its own DCC and scenario 1b would be storing it on a gateway, which would then be able to store DCCs for multiple devices. Scenario 2 is to store a DCC for each sensor device in a central location in the IoT system, i.e., the server. Scenario 3 is to store DCCs outside of the IoT system, where scenario 3a would be that the company which does the calibration of the sensor, e.g., FORCE Technology, stores the DCC in the cloud where the customer can access it whenever it is needed. While scenario 3b would be for an organization further up the calibration hierarchy to store the DCCs. See also Figure 6.

Each of these scenarios have different challenges which will not be described in depth, but a few examples are given. For scenario 1a and 1b a challenge could be hardware requirements since a full DCC as described above can be a large file relative to the hardware of IoT sensor devices. But perhaps storing a partial DCC on each device could be beneficial. For example, if the measurement adjustments are made on the device, then the data arriving at the platform for analysis is already adjusted. Scenario 2 generally seems to be a good solution as the DCCs are stored centrally where there is more storage capacity and computing power.

The storage location also depends on the process of creating the DCC since in some cases it would also be natural to have the company doing the calibration store it and perhaps make it available for the customer in the cloud. But something else might be needed if devices are bought off the shelf. Then the sensor devices could ship with built-in DCCs or the seller could make the DCCs available online.

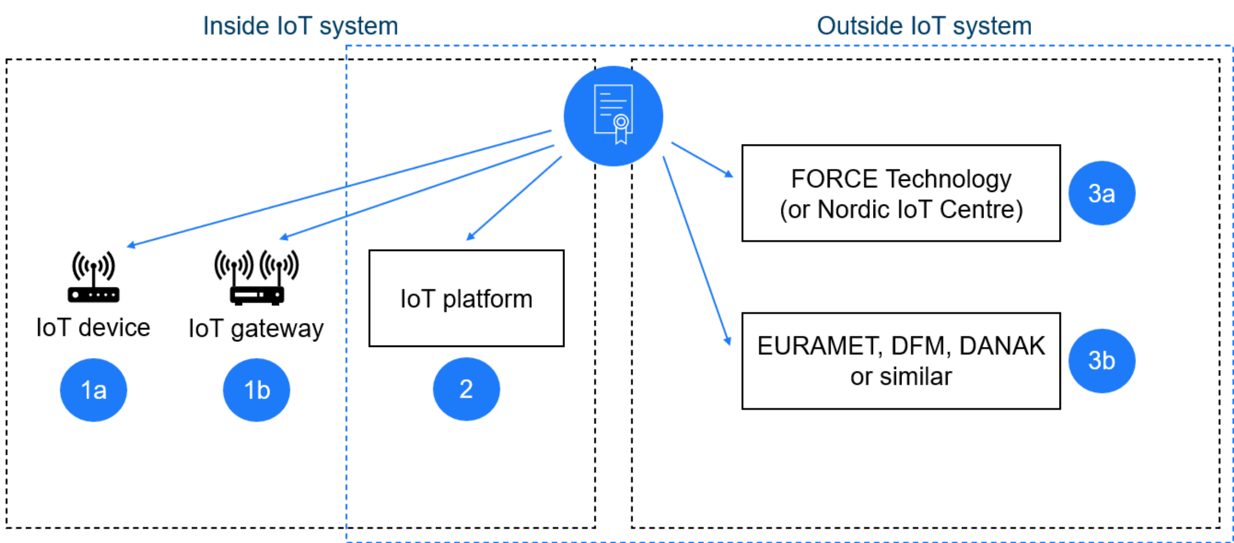


Figure 6: Different scenarios of storing DCCs for an IoT use case. The location can vary from the IoT device itself to an online database of the calibration laboratory. Combinations between the individual locations can also exist.

3.3. Field or In-Situ Calibration

In IoT systems it is, more often than not, the case in recent years that small and low-cost sensors are used to accomplish the monitoring needs. A typical example of such sensors are the ones monitoring ambient quantities, particularly concerning both indoor and outdoor air quality. In this category one can find sensors for gas pollutants (CO_2, O_3, etc.) and sensors for dust particles (particulate matter sensors). However, there are many concerns regarding these low-cost sensors and one of them is the quality of the measurement data they produce.

One classical solution to this is to periodically recalibrate the sensors in a calibration laboratory. This approach has many challenges, both economically and practically, in the context of the IoT world though, where it will not be unusual in the future to have deployments of hundreds of sensors. It was additionally observed by some researchers that even if laboratory calibration is performed, such instruments may behave differently in the field.

Therefore, multiple solutions have been proposed in the literature by researchers, performing what is called *field or in-situ calibration*. This term is used to describe situations where measuring sensors are calibrated while deployed in the field, preferably without human intervention, by using values provided by other sensors deployed in the same network. There are many characteristics that could be attributed to a sensor network and equally many classification sub-categories for the field calibration algorithms, but the most prominent is the presence of reference sensors.

Based on this characteristic, there are three categories of field calibrations found in the literature [6], [7], also depicted in Figure 7. When a sufficient number of reference devices is present, the calibration is called **reference-based** or **non-blind calibration**. On the opposite side we find the calibration of sensor devices in the absence of reference values, which is called **blind calibration**. Lastly, there is also the hybrid situation that is called **partially blind calibration**, where the sensor to be calibrated receives reference information to calibrate itself either from a subset of other devices or from pre-calibrated devices.

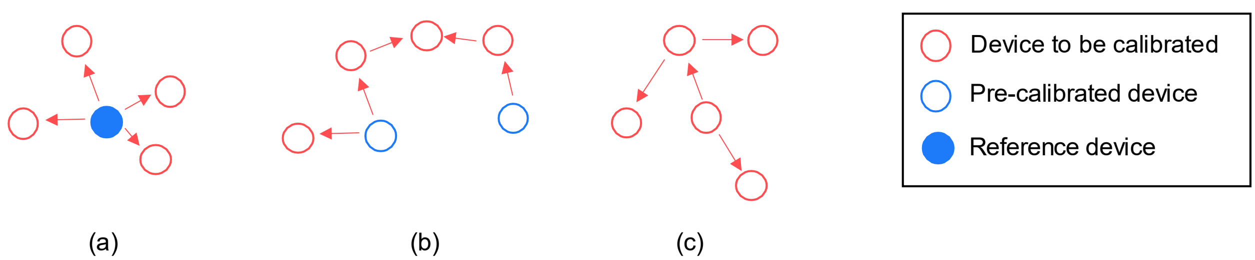


Figure 7: There are three categories of field-calibrations, based on the presence of reference data: (a) Reference-based, (b) partially blind, and (c) blind

The most straightforward of these categories is the reference-based calibration, which is also the most reported in the literature. Moreover, this approach is the closest to a "traditional" calibration approach with measurement standards in the laboratory. The easiest way to implement such a calibration is by directly co-locating reference sensors in the field with non-reference devices for an extended period to achieve their calibration. The reference sensors might be calibrated instruments or simply sensors with a known uncertainty.

In the case of air quality low-cost sensors for example, such sensors might be calibrated in the field by co-locating them with governmental monitoring stations that measure the same measurands with high precision and are regularly re-calibrated.

The measurement data collected during the co-location period by the non-reference and the reference sensors are used to develop regression models, using either single or multiple parameters. Another approach would also be to use the collected data to develop and train a neural network or a decision-tree-based algorithm or similar.

Figure 9 and Figure 10, taken directly from [8] without modifications, demonstrate how the in-field calibration with co-location with a reference sensor improves the accuracy of a low-cost $PM_{2.5}$ sensor. Figure 8 compares the uncalibrated low-cost sensor and the reference sensor and the low accuracy of the former is obvious. The graph in Figure 9 compares the same low-cost sensor, after having been calibrated, with the reference sensor. The improvement of the sensor's accuracy is obvious.

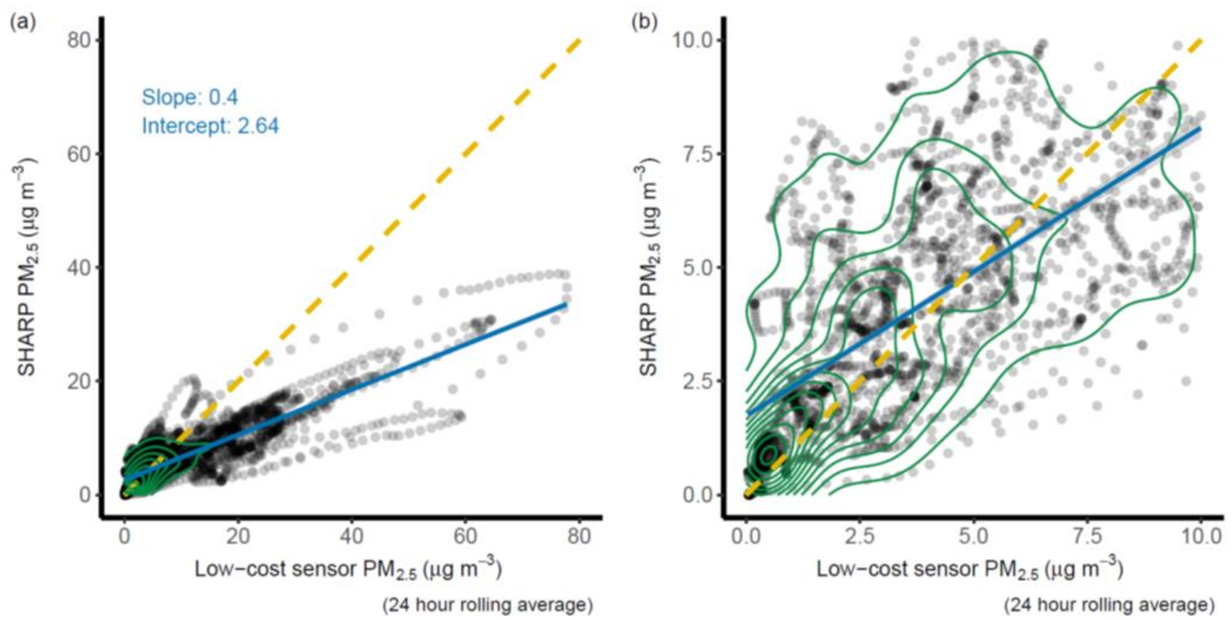


Figure 8: Graph showing the difference between the $PM_{2.5}$ concentration measurements of a low-cost sensor and a collocated, calibrated reference sensor (SHARP). The deviation of the regression line (solid blue) from the 1:1 line (yellow dashed) shows how inaccurate the low-cost sensor is. Reproduced from [8] without modifications, licensed under [CC BY 4.0](CC BY 4.0).

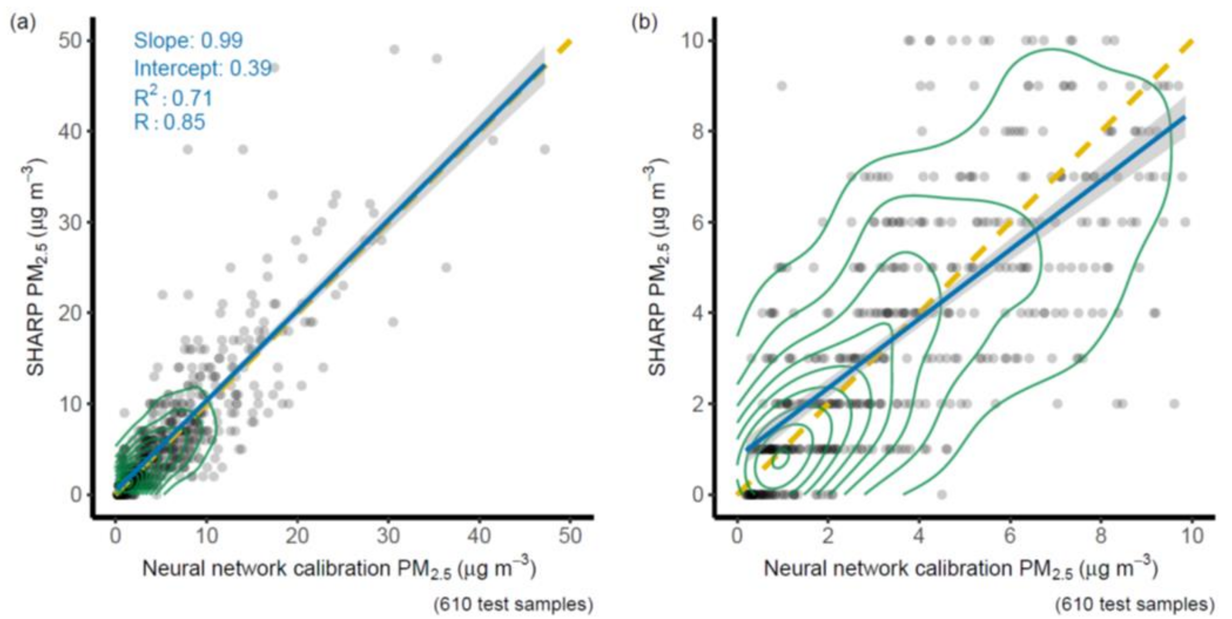


Figure 9: The graph compares the $PM_{2.5}$ concentration measurements of an in-situ reference-based calibrated, low-cost sensor with a collocated, calibrated reference sensor (SHARP). The regression line (solid blue) came very close to the 1:1 line after the calibration. Reproduced from [8] without modifications, licensed under CC BY 4.0.

3.4. Component Choice

In some cases, the accuracy of IoT measurements can be improved simply through the choice of components and sensors used in the measurement devices.

In this context, the use of digital sensors should be analyzed, as opposed to using analogue ones. With the advancement of microelectronics in the recent years, it is now possible to find digital microsensors that haver many advantages compared to their traditional analogue counterparts. When seen from the metrological point of view, these digital sensors offer a more straightforward way to take high precision measurements.

Let us take the example of temperature sensing. One typical way of monitoring temperature is by using Resistance Temperature Detector (RTD) sensors. These are analogue sensors, which are among the most accurate temperature sensors available, but require additional components for their operation and significant effort to achieve the desired accuracy. Usually a precision analog-to-digital converter (ADC) and an accurate reference resistor are used and in turn, getting accurate measurement circuits with these ADCs requires attention to detail in design of measurement circuits and calculation of the measurement. Once the whole signal chain circuit has been designed, the only way to know its accuracy is by calibrating the entire system. This process will also compensate and correct the strong non-linearity that RTD sensors typically have.

Having the RTD sensors as our reference point, let us see what can offer the microchip digital sensors that under certain conditions could replace the RTD sensors. First of all, such components combine the sensing part with the analog and digital signal processing circuitry on a tiny silicon chip. This results in enhanced reliability and precision, mainly because the weak analog sensor signals can be amplified and digitized with high precision directly where they are generated. Second of all, having a complete sensing system in a single component enables the suppliers to factory calibrate such sensors and store the calibration parameters to the chip's own memory. In many cases there are microchip digital sensors that are factory calibrated with traceability, so that the end-user can be confident about the achieved accuracy and uncertainty without additional calibrations being necessary. Lastly, it is easier for the digital sensors to incorporate features like temperature compensation, self-tests, and linearization.

The TMP117 digital temperature sensor with NIST traceability from Texas Instruments [9] is a good example that illustrates how the component choice can influence the measurements accuracy. In Figure 2-2 of [10], the reader can find a chart comparing the raw accuracy of TMP117 with RTD sensors of different accuracy class, where it can be seen that TMP117 is comparable in accuracy to the Class AA RTD. As also mentioned earlier in this section, it is expected that the RTD system will in the end be less accurate than the TMP117, due to the major effect that various parameters will have on the RTD system accuracy (such as the ADC selection, layout of signal traces, component tolerances etc.)

3.5. Sensor Installation

Another method of improving the accuracy of the IoT sensor measurements is related to the installation of the sensor. It can be often overlooked, but the sensor installation can heavily influence the accuracy of both the raw data and the final results of the application.

First, the location or position where the sensor is installed plays an important role on how representative of the measurand will the measurements taken by this sensor be. If the location or position is poorly selected, then the sensor will produce data that will not show the real value of the physical phenomenon that is being monitored. This will naturally mean that the application outcome will be inaccurate.

An example where the installation position is very important to the measurement accuracy are the Particulate Matter (PM) sensors, which is an air quality sensor ("PM" is a mixture of airborne solid particles and liquid droplets that can be inhaled). When these sensors are used to monitor the ambient air quality levels, then certain requirements exist in regard to the sensor location. First, the sensors should be placed somewhere with unobstructed air flow. Otherwise, the sensor might measure inaccurately the air quality.

Moreover, the PM sensors should be placed in accordance with the European parliament's legislation on air quality, which states, as for instance, that a sensor should be placed at a height of 1,5m to 4m [11]. The objective here is to avoid dust resuspension, which might happen if for example somebody is passing by the sensor. Moreover, the sensor should be installed at a certain distance from roadways, depending on the daily traffic [11].

Another similar example can be given with the air pollutant sensors, such as NO_2. Placing the sensor in the vicinity of local minor sources of these pollutants can cause high concentrations of the pollutant. If the monitoring objective of this sensor is to determine the air quality of a large area, it should be thus avoided to place the sensor near local, minor sources.

An additional factor related to the installation that might influence the measurement accuracy is the quality of the installation. A typical example in this category are the strain gauges. Due to their high sensitivity, any errors during the installation will result in inaccurate or unreliable data. Such errors could occur for example during the surface preparation (e.g., insufficient cleanliness of surface), the bonding (e.g., wrong adhesive or insufficient curing conditions), the soldering (e.g., contaminated solder tip, too much solder or residual flux), or the protection (e.g., insufficient protection). It is therefore important to ensure an optimal installation (strain gauge properly bonded and protected against all environmental influence factors, and the connection-cables optimally chosen) in order to achieve the promised measurement accuracy.

High-precision silicon digital temperature sensors, such as the ADT7422 or the TMP117, impose also certain requirements regarding their installation, if high accuracy measurements are desired. First, stresses on the die can hugely affect the accuracy of the sensor, therefore things like thermal expansion of the PCB, soldering or not of the exposed thermal pad, as well as the soldering process in general should be considered. Second, the self-heating effect of the sensor should also be carefully considered for precise measurements.

Although these sensors are usually ultra-low power devices, there is always some power dissipated as heat when the internal ADC is converting, which can be noticeable with a higher supply voltage and higher measurement frequency. This heat can then induce a drift to the temperature measurements (see for example Figures 8-2 and 8-3 from [9]). Among other things, one way to minimize the effect of self-heating is to use a PCB layout that provides minimal thermal resistance to the measured object surface or the surrounding air. Lastly, an additional consideration relevant to the installation of these digital temperature sensors is related to the monitoring objective, namely whether it is desired to measure solid surface, moving air, or still air temperature. In this context one should carefully consider the layout of the PCB where the sensors are mounted, as well as the design of the device's mechanical enclosure, and adapt them to the monitoring need. For example, if the device is used to measure moving air temperature, an important consideration is to use a PCB with increased thickness, since an increased thickness, will increase the PCB thermal mass and in turn reduce measurement noise from the temperature fluctuation inside the air stream.

Preconditioning of the measurand could also be included in the sensor installation category. Here the measurand is manipulated before being sensed in a way that will improve the measurement accuracy. For instance, we can take the case of the measurements from low-cost optical PM sensors being negatively affected by high levels of ambient relative humidity. What is happening in reality is that the air particles are expanding due to the absorbed water and this affects the accuracy of the measurements. The problem can be addressed by installing a heater together with the sensor, so that the air intake is heated and all its moisture evaporates before the measurement takes place. In fact, this is one of the features that the expensive and high-accuracy PM sensors have.

3.6. Continuous Self-Validation

One significant and common source of error related to sensors is drift. This can either result in a bias, i.e. repeatable values, that are too low or too high, or in increased inaccuracies. Drift over time is a natural phenomenon that all sensors are susceptible to, regardless of the vendor, price, or accuracy. It might be caused by natural decline of the sensor itself, by decay due to exposure to chemical or other contaminants, or simply by the expansion and contraction when subject to humidity and temperature cycles. The mechanical installation might also be a source of drift.

The existence of such an error is unavoidable, but what is different from sensor to sensor is how big it is or how large impact it has. Sometimes it is so small and/or a slow evolving process that it doesn't significantly affect the accuracy of the measurements during the lifetime of the sensor. In other cases, the drift might bring the sensor "out of tolerance" or "out of calibration", and this might make the sensor data unreliable and compromise the operations.

Figure 10 is a demonstration of how much the devices can drift over time. On the left side, in panel (a), one can find the distribution of the Weighted Mean Error (WME) for a batch of new gas meters, calculated according to OIML R137-1&2:2012, after the meters are adjusted to comply with the relevant regulations and before being sent to the field. Panel (b) on the right hand-side depicts the distribution of the WME for the same batch of meters, after having been recalibrated at the schedule interval. The WME after the initial adjustment has a normal distribution with a standard deviation of around 0.07 %, whereas the standard deviation of the WME after the recalibration increases to around 0.46 %.

It is obvious from this example that the drift during the two calibrations had caused some of the sensors to go "out of calibration".

There are two main strategies to detect the sensor drift, either by calibrating the sensor or by using self-validating methods and algorithms.

The most effective and reliable one is to calibrate the sensor. Through the calibration process the sensor output will undergo comparison to the output of a calibrated reference sensor, and therefore the level of the drift will be revealed. If necessary, the offset caused by the drift can then be adjusted.

More often than not, the re-calibration of the sensor takes place in predefined time intervals. This implies that the calibration doesn't happen when it is needed, but it is usually driven simply from the supplier's recommendations or common practices. This can undoubtably lead to suboptimal calibration intervals and high costs. It is hence desired to develop methods and processes that use real data collected from the sensors to define optimal calibration intervals based on a number of parameters, such as risk and economy. FORCE Technology has recently addressed this topic through the R&D project *RiskKAL – Risk and needs-driven calibration strategies*, funded by the Danish Agency for Higher Education and Science, with the purpose to define such new strategies [12].

Such risk-based calibration strategies can be enabled by collecting secondary data from the sensor. These secondary data could be information about the environmental conditions during the sensor operation, the sensor's own temperature or self-heating effect, and the sensor's power consumption. Analyzing the secondary data can help the device owners in understanding whether there are indications that the sensor might develop high drift, such that its accuracy can be compromised.

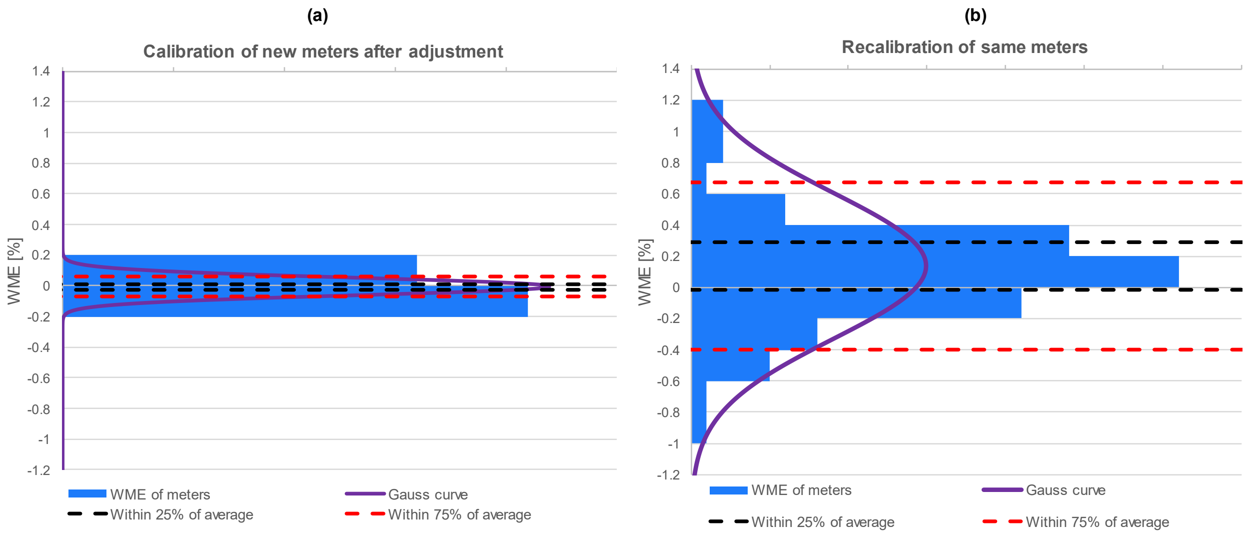


Figure 10: Distributions of the weighted mean error for a batch of new gas meters (a) right after initial calibration and adjustment to comply with the applied regulations (and before sent to the field) and (b) when coming back for a scheduled recalibration. Source: FORCE Technology, gas meters calibration facilities

Although being the most effective way to detect sensor drift, in some cases, as discussed earlier (see Section 3.3), it might not be desired or feasible to perform periodic re-calibrations of the deployed IoT sensor devices. Then a, sensor-level or network-level, self-validation or drift self-detection strategy might be an acceptable alternative.

One way to implement this strategy is to apply redundancy. A device could for example have two (or more) sensors of the same or different technology that measure the same measurand. Then the device can monitor the differential between the readings of the two sensors and detect when the readings drift apart more than a normal range. A warning can then notify the user that some action is potentially required.

There is no reason why, in principle, this strategy cannot be extended further up the system to the sensor network level, where the concept of soft sensor models or virtual sensors can be applied. The measurement data of multiple redundant and correlated sensors can be used to develop models that can infer when a sensor in this network is drifting excessively out of the desired range. The sensors can be correlated either naturally, such as when installed on a single structure like a water pump, or in a different way, such as spatially as in the case of ambient air temperature sensors located in the local geographical area.

On a final remark to the topic of self-validation, we should point out that one should be cautious of how to implement and how to use such a method. For example, let us briefly look at the ABC algorithm, which stands for Automatic Baseline Correction. This algorithm is used to self-correct the drift in CO_2 sensors. Its operation assumes that over a period of some days, the lowest measured CO_2 concentration is approximately 400 ppm (or 0.04% vol), which corresponds to fresh air. But exactly this is also its weak point, since there is no other way to test if this assumption is correct or not. Therefore, it is subject to errors and its applicability should be evaluated from case to case. Having a reference station in the vicinity can of course enhance the algorithm, by performing comparisons between the station's and the sensor's measured values.

3.7. Monitoring of Operating Conditions

Except for the drift, which is discussed in Section 3.6, there are also other error sources that could deteriorate the sensor measurement. For example, it is well-known that the low-cost optical PM sensors that are becoming more and more popular in the recent years are significantly affected by the levels of relative humidity in their environment [13]. Especially at very humid conditions, the reported concentrations from these sensors are usually much higher than the reference values. Figure 11, reproduced from [13], shows how during times with high RH (> 90 %) the low-cost Alphasense OPC-N2 sensor recorded $PM_{2.5}$ concentrations considerably higher than that measured by the high-accuracy reference sensor TSI 3330.

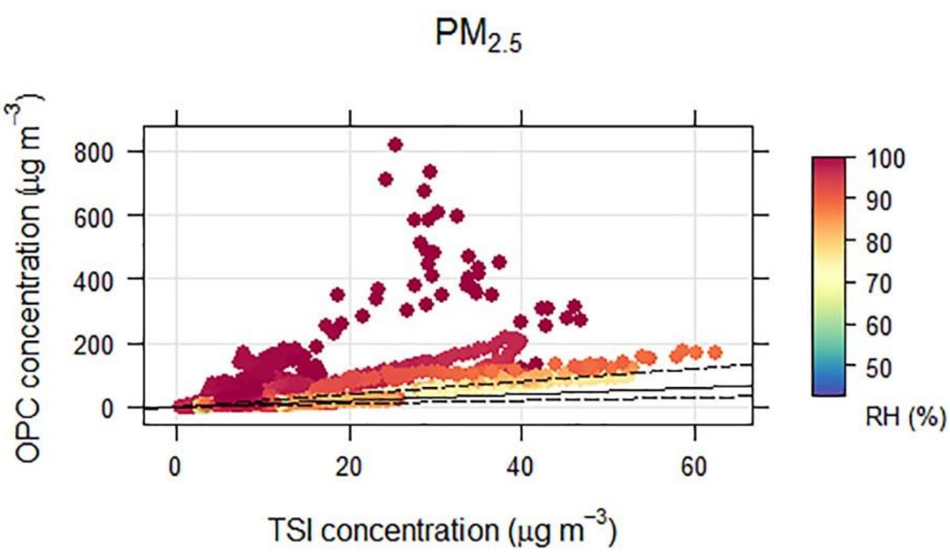


Figure 11: Comparison of the measured $PM_{2.5}$ concentrations by a calibrated reference sensor (TSI 3330) to the concentrations measured by low-cost sensors (Alphasense OPC-N2), with color gradient from the ambient relative humidity. Reproduced from [13] without modifications, licensed under CC BY 4.0.

Figure 12 contains a similar example, where the effect of the ambient relative humidity on the measurements of the low-cost OPC sensor is obvious.

In situations like this, where the error source doesn't have a permanent effect (like drift over time), the optimal way to address the issue is to develop validation algorithms. These would be able to detect when the sensor is generating inaccurate measurements and urge the system for action. The system, in turn, could either apply corrections -if possible- to compensate for the errors, or classify the measured data as "low accuracy" data.

If we were to further analyze what types of algorithms can be used for sensor validation, we would find different approaches. Three examples of the used approaches are given here.

First, such a validation algorithm could be based on monitoring the environmental conditions that are proven to affect the sensor operation, such as the temperature and relative humidity. For example, the authors in [13] and [14] have developed such correction algorithms that compensate for the negative effect of relative humidity on the accuracy of low-cost ambient particulate matter sensors. In Figure 13 and Figure 14, reproduced from [14], the improvement from these algorithms on the accuracy of the sensors is evident.

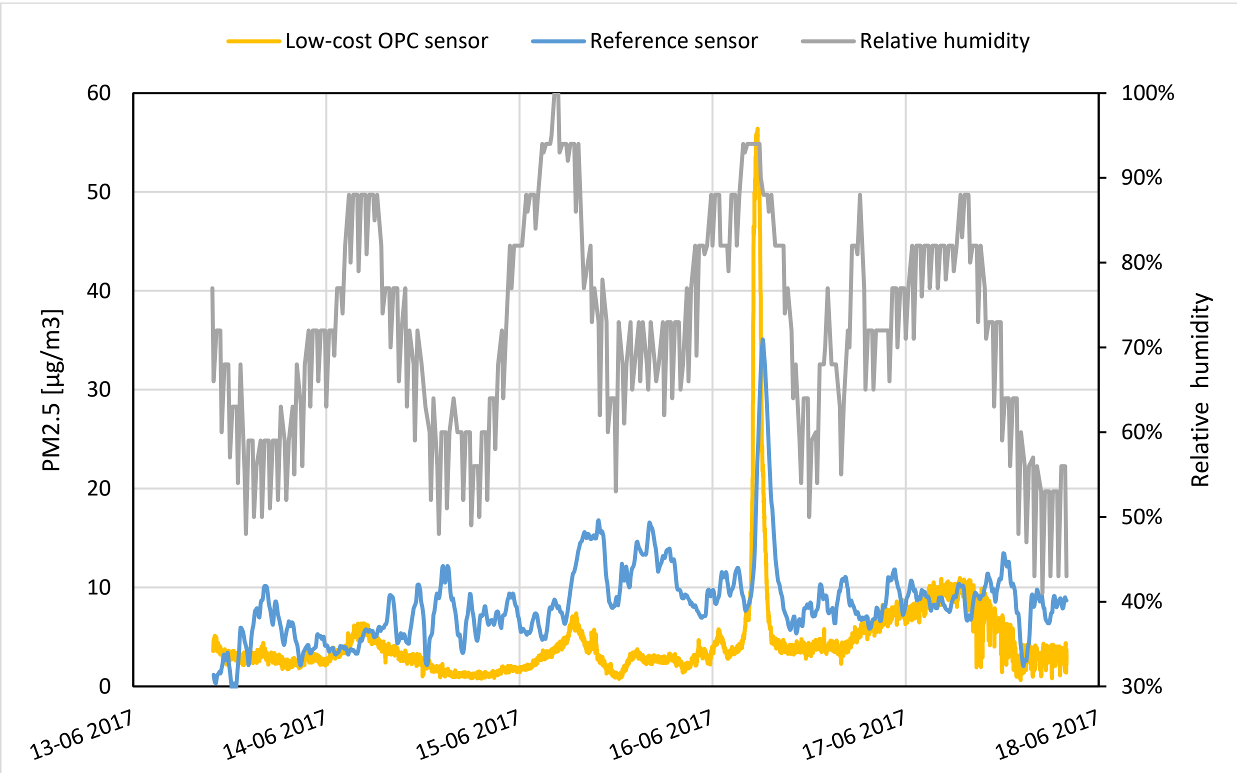


Figure 12: Graph showing the influence of environmental conditions (relative humidity more specifically) in the PM2.5 measurements of a low-cost Optical Particle Counter sensor without a drying system on the sampling inlet. High values of relative humidity have a clear effect on the sensor's output, compared to the output of the reference sensor. Source: FORCE Technology, business unit of Clean Air Technologies.

Second, systemic knowledge of the installation location and its conditions can also help in developing a model where the sensor readings are compared to the expected readings in the specific location.

Third, a validation algorithm could be based on comparisons between the sensor under focus and other sensors that give the same information. As an example, for a novel livestock weighing application based on camera images, the validity of the measurements can be check against data from established measurement methods, which in this case could be the traditional weighing stations.

Lastly, similarly to what was described in the section about sensor drift, a validation method can be developed using correlation in a homogeneous sensor fusion, where sensor data of different or same type are combined to provide a common assessment of a measurand.

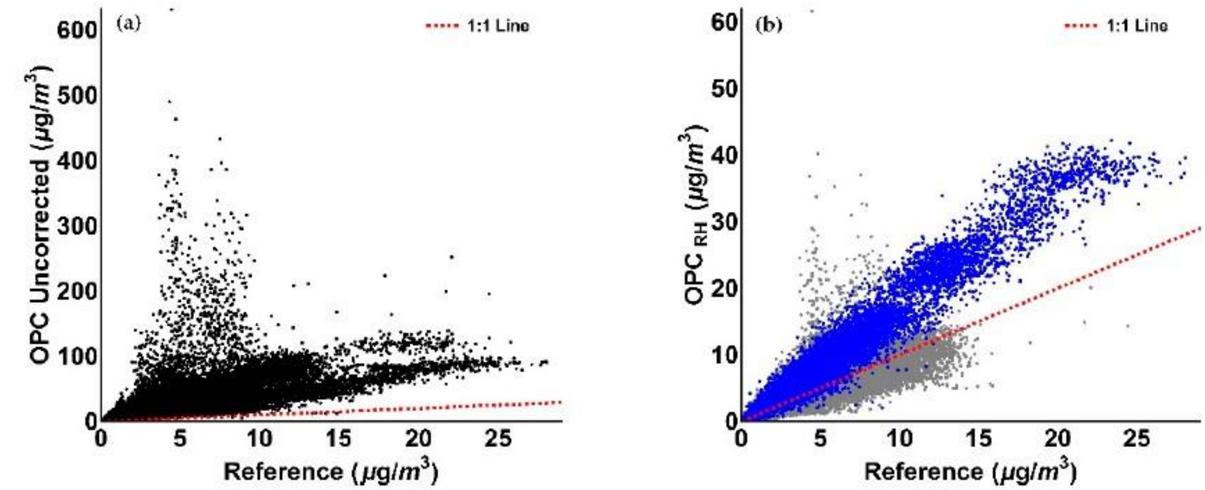


Figure 13: Scatter plots illustrating how an RH-correction algorithm improves the $PM_{2.5}$ measurements of a low-cost OPC sensor. The blue colored points in (b) correspond to a time period that the authors identified as having different PM composition. Reproduced from [14] without modifications, licensed under [*CC BY 4.0*](#).

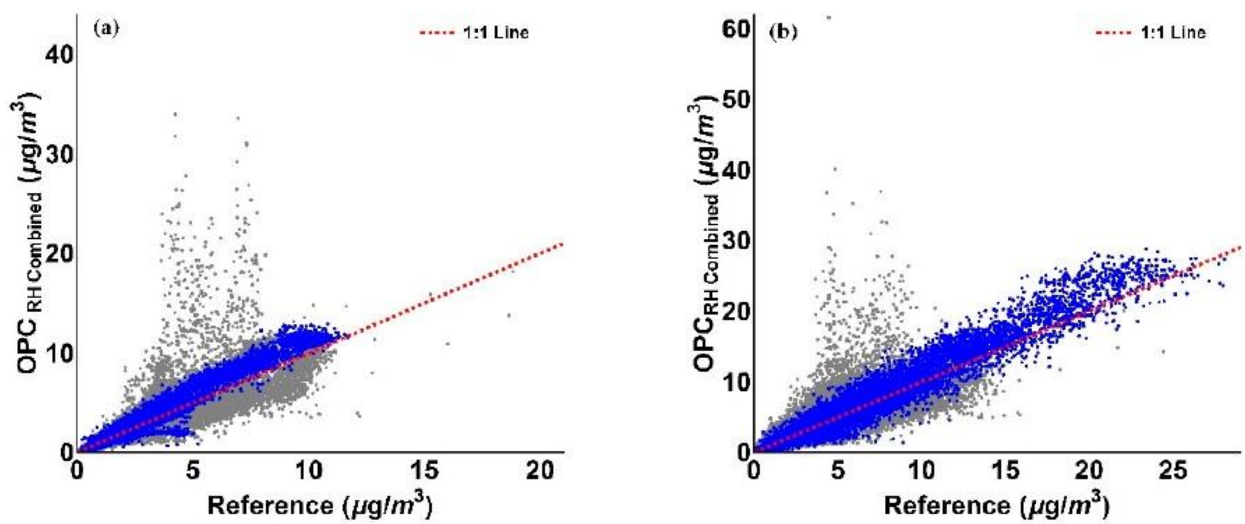


Figure 14: Scatter plots of the RH-corrected (a) PM_1 and (b) PM2.5 concentration measurements of a low-cost OPC sensor compared to reference concentrations. Additional corrections to account for the difference in PM composition have further improved the accuracy compared to Figure 13. Reproduced from [14] without modifications, licensed under [*CC BY 4.0*](#).

3.8. Digital Twins and Simulations

The digital twin technology can be another tool that can be used in the context of metrology for IoT. In digital twins a virtual representation of the physical IoT sensor is created, serving as the digital counterpart of the device. As such, the sensor outputs can be simulated and predicted with accuracy. This model can be used in multiple ways.

One way is to use the digital twin and the simulations in order to predict the behavior of the device under different external conditions. For example, the digital twin can be introduced to various known error and noise sources (e.g., dust on lenses of a camera, poor lighting, excessive moisture) and then it can be observed how much the accuracy of the sensor changes under these conditions. In this way, the calibration policy can change from scheduled-based to condition-based or even predictive.

The digital twins can also be used during the operation of the IoT sensor, after its deployment in the field. By comparing the measured data from the physical device with the output of its digital twin, out-of-calibration events can be detected.

3.9. Systems Hard to Calibrate

Alongside the examples and methods give in the previous Sections, there are also some IoT applications that deserve extra attention. These are systems that are hard or even impossible to calibrate.

As an example, let us assume for a moment that we are coping with an application where cameras are applied to estimate the weight of livestock, be it sheep or pigs, with the purpose of monitoring their development. Such a task would be otherwise manually performed by the farmers using weighing stations. But the question arises: how can one improve the accuracy of such devices? It is in fact not possible to calibrate such a sensor system in the laboratory. The reason is simple: what kind of accredited measurement setup shall be used? For example, the weight standards used in the FORCE Technology laboratory for product compliance related to weighing can only be applied in system where the weighing process is based on gravity. This obviously is not the case with the above mentioned IoT system.

When in general there are IoT systems that base their operation on A.I. algorithms (or other algorithms), then the calibration of such a system is challenging. The same is also true for systems that operate on the principle of the *virtual sensor*, where many sensors are measuring the same or different measurands and the system combines all the information to form a common “sensor” that doesn’t exist physically. An example of such system can be a traffic monitoring system with cameras or an Overall Equipment Efficiency system for a production line. In these cases, the individual sensors and the raw data they are generating can perhaps be calibrated (although not always), but the system-level output is hard to calibrate.

4. Conclusions

As the IoT systems are infiltrating more and more our everyday lives and the modern industrial production and supply chains, poor data quality is becoming apparent as a major problem. The traditional methods for ensuring traceability to the measurement standards maintained by the national metrology institutes usually involve calibrations in accredited laboratories. However, these methods are typically not feasible for direct application in IoT systems, from a technical and/or financial point of view. Additionally, the focus in this first period of adoption of the IoT technologies has been more on how to collect data and not so much on how good they are.

For this reason, various research entities around the world have been focusing on approaching the data quality issue in wireless sensor networks by proposing methods for in-field calibrations. Metrology is also undergoing a digital transformation, mainly with the development and adoption of the digital calibration certificates, a process which will improve the applicability of metrological traceability in the IoT systems. Moreover, there are research efforts studying the effect of various environmental conditions on low-cost sensors.

Based on the above research topics but also on the experience and industry exposure that FORCE Technology has in various application domains, we have created a set of methods and best practices related to the improvement of data quality in the IoT systems. The proposed toolbox is applicable in different stages of the lifetime of an IoT system, starting from the design phase and manufacturing and going up to the deployment and operation. It is important for an IoT system designer or user to be able to identify when actions need to be taken and what can be done at each stage. It is also equally important to identify how much accuracy a system needs and where do the requirements come from.

Bibliography

[1] American Society for Quality (ASQ), "Cost of quality (COQ)," [Online]. Available: https://asq.org/quality-resources/cost-of-quality. [Accessed 9 July 2021].

[2] EURAMET e.V., Technical Committee for Thermometry, "Guidelines on the Calibration of Temperature Block Calibrators," 2017.

[3] T. Mustapää, P. Nikander, D. Hutzschenreuter and R. Viitala, "Metrological challenges in collaborative sensing: Applicability of digital calibration certificates," *Sensors,* vol. 20, no. 17, pp. 1-19, 2020.

[4] C. Brown, T. Elo, K. Hovhannisyan, D. Hutzschenreuter, P. Kuosmanen, O. Maennel, T. Mustapaa, P. Nikander and T. Wiedenhoefer, "Infrastructure for Digital Calibration Certificates," *2020 IEEE International Workshop on Metrology for Industry 4.0 and IoT, MetroInd 4.0 and IoT 2020 - Proceedings ,* p. 485–489, 2020.

[5] T. Mustapaa, J. Autiosalo, P. Nikander, J. E. Siegel and R. Viitala, "Digital Metrology for the Internet of Things," *GIoTS 2020 - Global Internet of Things Summit, Proceedings,* 2020.

[6] F. Delaine, B. Lebental and H. Rivano, "In Situ Calibration Algorithms for Environmental Sensor Networks: A Review," *IEEE Sensors,* vol. 19, no. 15, pp. 5968 - 5978, 2019.

[7] J. Barcelo-Ordinas, M. Doudou, J. Garcia-Vidal and N. Badache, "Self-Calibration Methods for Uncontrolled Environments in Sensor Networks: A Reference Survey," *Elsevier,* vol. 88, pp. 142-159, 2019.

[8] M. Si, Y. Xiong, S. Du and K. Du, "Evaluation and calibration of a low-cost particle sensor in ambient condition using machine-learning methods," *Atmospheric Measurement Techniques,* vol. 13, pp. 1693-1707, 2020.

[9] Texas Instruments, "Datasheet of TMP117," [Online]. Available: https://www.ti.com/lit/gpn/tmp117. [Accessed 9 July 2021].

[10] Texas Instruments, "Application Note: "RTD Error Minimization and Alternative Measurement Methods"," [Online]. Available: https://www.ti.com/lit/pdf/snoaa67. [Accessed 12 July 2021].

[11] Den Europæiske Unions Tidende, "EUROPA-PARLAMENTETS OG RÅDETS DIREKTIV 2008/50/EF "Om luftkvaliteten og renere luft i Europa"," 2008.

[12] FORCE Technology, "RiskKAL R&D project," FORCE Technology, [Online]. Available: https://forcetechnology.com/en/innovation/completed-projects/risk-and-needs-driven-calibration-strategies-riskkal. [Accessed 13 July 2021].

[13] L. R. Crilley, M. Shaw, R. Pound, L. J. Kramer, R. Price, S. Young, A. C. Lewis and F. D. Pope, "Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring," *Atmospheric Measurement Techniques,* vol. 11, pp. 709-720, 2018.

[14] A. Di Antonio, O. A. M. Popoola, B. Ouyang, J. Saffell and R. L. Jones, "Developing a Relative Humidity Correction for Low-Cost Sensors Measuring Ambient Particulate Matter," *Sensors,* vol. 18, no. 9, 2018.

[15] H.-J. Chu, M. Z. Ali and Y.-C. He, "Spatial calibration and PM2.5 mapping of low-cost air quality sensors," Nature, 2020.

[16] K. Sadighi, E. Coffey, A. Polidori, B. Feenstra, Q. Lv, D. K. Henze and M. Hannigan, "Intra-urban spatial variability of surface ozone in Riverside, CA: viability and validation of low-cost sensors," *Atmospheric Measurement Techniques,* vol. 11, pp. 1777-1792, 2018.

[17] *CFR, Part 58, Appendix E, "Probe and Monitoring Path Siting Criteria for Ambient Air Quality Monitoring".*

[18] FORCE Technology, "Monitoring of corrosion in reinforced concrete extends service life," [Online]. Available: https://forcetechnology.com/en/services/probes-and-measuring-equipment-for-corrosion-monitoring-of-steel-reinforcement. [Accessed 14 July 2021].

[19] S. Eichstädt, M. Gruber, A. P. Vedurmudi, B. Seeger, T. Bruns and G. Kok, "Toward smart traceability for digital sensors and the industrial internet of things," *Sensors,* vol. 21, no. 6, pp. 1-15, 2021.