Environment Administration

City of Gothenburg

The LoV-IoT project: Air and water monitoring with Internet of Things

Air quality sensors

Report number R2020:18

Preface

The project Air and water monitoring with Internet of Things, LoV-IoT, is an innovation- and development project which has examined the possibilities in using sensors and Internet of Things to develop the environmental monitoring of air and water within cities. One aim of the project was to develop an effective system for gathering information on air and water quality in cities to contribute to better health among the citizens.

The project was running for three years, between autumn 2017 until autumn 2020 and it was financed by the Strategic Innovation Program IoT Sverige, as a part of their work within IoT for societal benefits.

This report describes the work done within work package four and will answer to the deliverables within that work package. The report is written by IVL Svenska Miljöinstitutet, together with Vinnter, RISE, Insplorion, The City of Uppsala, Centro Mario Molina, Chile and the City of Gothenburg.

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Air quality sensors

City of Gothenburg, Environment Administration

Author: Jenny Lindén (IVL), Ågot Watne (Göteborgs Stad, miljöförvaltningen), Pedro Oyola (CMM Chile), Martin Giebat (Vinnter), Kristina Fogel (RISE), Dimitar Kolev (RISE), Marta Segura Roux (IVL Svenska miljöinstitutet) Ida Gottberg (Uppsala kommun), Olof Andersson (Insplorion), Johanna Rieck Jilden (Göteborgs Stad, miljöförvaltningen) och Mehdi Ghalebani (Ericsson).

Photos: The LoV-IoT project

ISBN No: 1401-2448

If you want to use text or images from this report, please quote:
The City of Gothenburg, R2020:18 The LoV-IoT project: Air and water monitoring with Internet of Things Air quality sensors

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Summary

The overall objective of the air quality part of the innovation project LoV-IoT, was to assess possibilities for using low cost sensor technology in flexible observational platforms for monitoring urban air quality. Available low-cost sensor and communication technology was evaluated, and an observational platform was developed using suitable components. To allow real time communication of high-quality data, calibration and post processing needs were assessed and integrated in the platform.

The main lessons learned from this project are that low cost sensors potentially have many benefits, but it is important to understand the possibilities and limitations that this technology brings. This has been summed up in the following points:

- **Validate and post process the low-cost sensor data output to maximize data quality**.
  Data measured with low-cost sensors is commonly affected by biases such as systematic offset, influence by meteorological parameters, cross sensitivity to other pollutants and drift. To reduce biases and increase data quality, it is thus necessary to post-process the sensor data. This can be done by comparative measurements with reference instrumentation during representative ambient conditions. Based on these comparative measurements, correction algorithms can be developed and applied to increase data quality. We found that post processing algorithms developed for each individual sensor using machine learning techniques was required to optimize the data quality.

- **Limit the use of low-cost sensor technology to suitable applications where reliable and stable data quality can be assured**.
  The following suitable applications for the low cost sensor (LCS) technology were identified in the LoV-IoT project: in citizen science and for communication purposes, to complement and extend reference measurements, in studies of limited spatial and temporal extent, for identification of patterns rather than absolute concentrations, and for an initial rough measurement and indication, for example in an early warning system in situations when rapidly changing pollutant concentrations may occur.

Maximize flexibility and openness when integrating the sensor platform components to allow exchange of components.
With the rapid development of both LCS and communication technology, any sensor platform will rapidly be outdated, unless it is possible to exchange parts as new and improved alternatives are available. As low-cost sensor performance is still problematic, allowing exchange of components will ensure that the data quality can be improved as new solutions are available.

The LoV-IoT observational platform focuses on measurements of the pollutants that are most problematic in Swedish urban settings; nitrogen dioxide (NO_2) and particulate matter (PM_{10}, $PM_{2.5}$), as well as meteorological parameters, such as air temperature and relative humidity. Other components, such as CO_2 and SO_2 are also included in the tests, as well as noise sensors. The LUFT-NO2 sensor under development by

our LoV-IoT project partner Insplorion, has been included continuously in the development and evaluation of our LoV-IoT sensor platform. After testing and validation, the sensor platforms have been mounted in a number of different field settings in order to test their suitability for different applications as well as to assess the technology readiness level of the platform. The three main field applications that were assessed are:

1. Extending network of air quality measurement locations around major infrastructure projects. This has been a joint effort with the Swedish Transport Administration and has taken place at two main infrastructure projects in Gothenburg.
2. Extending the air quality station network in Chile and assessing potential use of sensors in early warning systems. Sensor platforms has been evaluated in both urban and industrial sites in collaboration with Centro Mario Molina (CMM) in Santiago, Chile. Initial findings have been published by Tagle et al. (2020).
3. Extend the current reference station network with additional measurement in locations of interest in Uppsala.

In addition to the development of the observational platform, additional, smaller sensor platforms have also been used in case studies as well as in LoV-IoT citizen outreach activities that aim to increase awareness and interest in air quality.

The work carried out in the LoV-IoT air quality monitoring work package will be described in this report. In the initial section, a general overview of the possibilities and limitations of using the rapidly developing low-cost air quality sensor technology for monitoring (Deliverable 4.1) will be discussed together with how adequate data quality have been reached for the developed LoV-IoT sensor platform. This is followed by a description of the development of the sensor platform from TRL 5 to TRL 6 (Deliverable 4.4) in Chapter 2. The data communication solutions used in the platform (Deliverable 4.2) are presented in Chapter 3, and the sensor selection and testing prior to platform integration (Deliverable 4.3) in Chapter 4. Finally, the testing and application of other sensor platforms for fixed and mobile measurement is described in Chapter 5.

Sammanfattning

Den huvudsakliga målsättningen med luftkvalitetsdelen inom innovations-projektet LoV-IoT var att utvärdera möjligheterna med att använda billig sensorteknik i flexibla sensorplattformar för att övervaka urban luftkvalitet. Kommersiella mikrosensorer och kommunikationsteknik utvärderades och flera mätenheter utvecklades med hjälp av lämpliga komponenter. För att göra kommunikation av högkvalitativa data möjlig i realtid, undersöktes behoven och kalibrering och efter-processering av mätdata integrerades.

De främsta lärdomarna från detta projekt var att billig sensorteknik kan ha flera fördelar, men att det är viktigt att förstå både möjligheterna och begräsningarna som den här typen av teknik ger. Detta har summerats i följande punkter:

- **Validera och efter-processera data från sensorerna för att maximera datakvaliteten**.
  Data som uppmätts med billig sensorteknik är vanligtvis påverkad av felkällor såsom systematisk offset, meteorologiska parametrar och korskänslighet för andra föroreningar och drift. För att minska felkällorna och öka datakvaliteten är det nödvändigt med efter-processning av sensordata. Detta kan göras med hjälp av jämförande mätningar med referensinstrument under representativa förhållanden. Baserat på dessa jämförande mätningar kunde algoritmer utvecklas och användas för att korrigera data och därför öka datakvaliteten. Vi konstaterade att det var nödvändigt att utveckla unika algoritmer för varje enskild sensor med hjälp av maskininlärning för att optimera datakvaliteten.
- **Begränsa användningen av billig sensorteknik till användning där pålitlig och stabil datakvalitet kan säkerställas**.
  Följande lämpliga användningsområden för billig sensorteknik identifierades inom projektet LoV-IoT: inom medborgarforskning och för kommunikationsändamål, för att komplettera referensinstrument, inom studier med geografiska begränsningar och tidsbegränsningar, för att identifiera mönster framför absoluta halter, för att få en initial grov mätning och indikation, till exempel i ett varningssystem i situationer där ändringar i föroreningshalter snabbt kan inträffa.
- **Maximera flexibilitet och öppenhet vid hopsättning av mätenheten för att möjliggöra ett byte av komponenter inuti enheten.**
  Till följd av den snabba utvecklingen inom billig sensorteknik och inom kommunikationsteknik, kan mätenheten relativt snabbt bli utdaterad, om det inte är möjligt att byta ut komponenter när nyare och förbättrade alternativ är tillgängliga. Eftersom prestandan hos billig sensorteknik fortfarande är problematisk, kommer utbytet av komponenter säkerställa att datakvaliteten kan förbättras när nya lösningar finns tillgängliga.

Sensorplattformarna som är framtagna inom projektet LoV-IoT fokuserar på mätningar av de föroreningar som är mest problematiska i svenska urbana miljöer; kvävedioxid (NO_2) och partiklar (PM_{10}, $PM_{2.5}$), samt meteorologiska parametrar såsom temperatur och relativ fuktighet. Andra ämnen, såsom CO_2 and SO_2, var också inkluderade i testerna. En av projektets partners, Insplorion, har

utvecklat en sensor “LUFT-NO2”, som har inkluderats kontinuerligt i utvecklingen och utvärderingen av sensorsplattformar i projektet LoV-IoT.

Efter att mätenheterna hade testats och validerats, monterades enheterna på ett antal olika platser ute i fält för att kunna testa sensorernas lämplighet för olika förhållanden samt för att utvärdera teknologins mognadsgrad. De tre huvudsakliga fälttesterna som utfördes var:

1. Ett utbrett nätverk av luftkvalitetsmätningar runt stora infrastrukturbyggen. Detta var ett samarbete med Trafikverket och har genomförts i två stora infrastrukturprojekt i Göteborg.
2. Ett utökat nätverk av luftkvalitetsmätningar där användningen av sensorer som varningssystem har utvärderats. Sensorerna har utvärderats både i urbana och industriella miljöer tillsammans med Centro Mario Molina (CMM) i Santiago, Chile. Initiala resultat har publicerats av Tagle et al. (2020).
3. Ett utökat nätverk. Det är ett komplement till de nuvarande referensstationer som är utplacerade på olika platser av intresse i Uppsala.

Som ett komplement till mätenheterna har också enskilda luftsensorer använts både i fallstudier och i aktiviteter mot medborgare, där målet har varit att öka medvetenheten och intresset kring luftkvalitet.

Arbetet som har genomförts i arbetspaketet kring luftövervakning i projektet LoV-IoT kommer att beskrivas i denna rapport. I introduktionsdelen av rapporten kommer vi diskutera möjligheter och begränsningar gällande användningen av billig sensorteknik inom övervakning (Leverabel 4.1). Även hur tillräcklig datakvalitet har uppnåtts för den framtagna LoV-IoT-mätenheten diskuteras. Vidare följer ett avsnitt i kapitel 2 i rapporten som beskriver utvecklingen av mätenheten från TRL 5 till TRL 6 (Leverabel 4.4). Datakommunikationen som användes (Leverabel 4.2) presenteras i kapitel 3, och val, test och hopsättningen av sensorerna (Leverabel 4.3) presenteras i kapitel 4. Avslutningsvis beskrivs testerna och applikationerna för andra enskilda sensorer för stationära eller mobila mätningar i kapitel 5.

Contents

1 Performance and applicability

The ongoing rapid technological development is radically expanding possibilities for monitoring the urban environment. Progress in sensor technology have provided smaller, often cheaper sensors for a multitude of applications – from monitoring of environmental parameters such as meteorology, air and water quality, to mapping of, for example, urban growth or activity, or in disaster evaluation. Perhaps equally important is the rapid development of data communication possibilities, often referred to as Internet of Things, IoT. This allows data to be communicated, often through wireless networks, continuously and with little manual interference required.

Application of this new sensor technology has gained strong interest for urban air quality, where monitoring is traditionally based on high precision measurements at fixed stations in accordance with European legislation and international standard methods. Data is generally collected with expensive, and often large and heavy instruments and the stations require regular maintenance to produce high quality data according to regulations. As a result, densities of official air quality observational networks are generally low, often with only one or a few stations representing the air quality of a whole city. Concentrations of air pollution at street level in an urban environment often varies greatly over short distances (e.g. Croxford and Penn 1998). Although the reference stations are carefully selected to represent similar urban environments, it may not capture variation in air quality due to changes in activity, such as a change in traffic flow or activity caused by infrastructure projects.

The representativeness of a single station, especially in a street canyon environment, is therefore generally limited to its near surroundings, especially in the often-heterogonous urban environment.

Although rapid development is ongoing in sensor technology in all price categories, the development of micro-scale low-cost sensors (hereafter LCS) is often in focus when smart solutions for monitoring the urban air quality are in focus. The use of LCS have also grown rapidly among the general public, and citizen science initiatives enables everyone with a Wi-Fi connection to set up a sensor and share air quality data globally. However, as is often the case with low cost equipment, there sensors tend to be less precise in correctly measuring the pollutant level, and less sensitive to changes in pollutant concentration compared to standard reference instrumentation. The performance of these LCSs is also often impaired by changes in meteorological parameters such as temperature or humidity, and they often react to changes in other pollutants than the one specified (Lewis et al. 2018). The importance of guidelines for data acquisition and quality control of the data from these platforms have therefore been stressed (e.g. Kumar et al. 2015; Moltchanov et al. 2015).

Technical development is however continually striving to provide solutions for increasing data quality, stability, and sensibility from these sensors. LCSs may thus come to provide future possibilities for a greatly increased spatial and temporal station network, as well as to allow for new, innovative monitoring methods and platforms that can be used to complement the existing reference stations.

Development of communication technology also allows for (near) real-time wireless data communication from sensors as part of the IoT network. Major benefits can be derived from deployment of IoT in smart cities and environ-mental monitoring, but there is an urgent need to address current limitations, including the interoperability of sensors, data quality, security of access and new methods for spatiotemporal analysis (Kotsev et al. 2016). Pending that data is reliable, this increases possibilities for rapid communication and assessment of relevant information, advice and visualization of air quality. This can be used to reduce response time for mitigation measures when concentrations are increasing, and communication with, for example, the general public. It also facilitates use of environmental data in planning urban development, in research and for commercial purposes.

1.1 Scientific evaluations of low-cost air quality sensors

A thorough understanding of the performance and limitations of the sensors used for observations is crucial to provide high quality data for analysis of air quality, and, as stated by Snyder et al. (2013), "data of poor or unknown quality is less useful than no data since it can lead to wrong decisions". The rapid development of LCS-technology for air quality calls for a continued intensive testing and validation of sensor performance (Lewis and Edwards 2016). As stated in a WMO financed study by Lewis et al. (2018), air quality LCSs are not currently a direct substitute for existing reference instruments or networks, but there are many specific monitoring needs where this technology could be beneficial if the associated limitations are carefully considered. Numerous studies have similarly concluded that LCSs have great potential for new strategies in air quality control, but that accuracy issues remain (e.g. Borrego et al. 2016; Borrego et al. 2018; Castell et al. 2017; Kocman 2018; Kumar et al. 2015; Rai 2017).

Lewis et al. (2018) concluded that there is scientific evidence that LCSs can be used for measurements of temporal and spatial variability in air pollution. However, LCS accuracy is currently likely insufficient for assessment of the concentration dependence of a specific chemical, and to accurately measure personal exposure. They also state that LCS are likely affected by environmental variables such as temperature or humidity and will likely require regular calibration and will show changes over the longer term, for example drift, change in sensitivity and selectivity of response. This is confirmed in the long-term study by for example Bai et al. (2019) who find a strong deterioration of sensor performance in a long term field calibration. In the EuNetAir Air Quality Joint Intercomparison Exercise, approximately 200 LCSs measuring a variety of pollutants were co-located and compared to reference instruments, showing significant differences in the results between and within different types of sensors and platforms In a follow up paper from the EuNetAir, the presented analysis suggested a possibility of compliance with the data quality objectives (DQO) defined by the European Air Quality Directive (2008/50/EC) for indicative measurements, if supported by adequate post processing

(Borrego et al. 2018). Studies presenting evaluation of LCS performance cover many different components, for example gases, such as NO, CO, CO2 and O3 (Castell et al. 2017; Fishbain et al. 2017; Kim et al. 2017; Munir et al. 2019; Spinelle et al. 2017a; Spinelle et al. 2017b; Topalović et al. 2019), particle matter (e.g.Bai et al.; Castell et al. 2017; Fishbain et al. 2017; Kim et al. 2017; Li et al.; Topalović et al. 2019), and VOC:s (Spinelle et al. 2017c). In the iCARUS project, an extensive summary of results from LCS performance evaluation up until the beginning of 2017 was presented (Rai 2017). The general conclusion from LCS-evaluation studies support the suggestion that relevant calibration and post processing is necessary to identify the useful, high quality data from LCSs.

An LCS evaluation toolkit presented by Fishbain et al. (2017) is aimed to evaluate a range of criteria to better assess their performance in varied applications and environments. This evaluation toolkit is openly available for application to any LCS tests. The need for frequent field calibration of LCSs is stressed by Kizel et al. (2018) and Rai et al. (2017), as the laboratory calibration risks not being satisfactory when sensors are deployed in the field, but also due to interferences with other pollutants, to sensitivity to environmental conditions, and to sensor aging and drift. Furthermore, Kumar et al. (2015) argues the need for data management algorithms aimed to collect information from the sensors and communicate only useful and reliable data to the end point. This is supported by Borrego et al. (2018), who concludes that LCSs have enormous potential for new strategies in air quality control, if supported by proper post processing and data modelling to ensure high data quality of the communicated end product. Using machine learning techniques, such as random forests or Artificial Neural Networks, has improved calibration results in comparison to applying linear or multiple regression (Smith 2019; Topalović et al. 2019; Zimmerman et al. 2018). However, as stressed by for example Haegler et al. (2018), it is important that predictor variables and models for calibration are not used in such a way that correction crosses from justifiable and empirical correction of the sensor data, to a predictive statistical model with little dependence on the sensor data.

Although no scientific consensus has been reached on how to evaluate, process and use data from LCS, guidelines for end users have been presented, for example by the EU Science Hub (Gerboles 2017), in the iSCAPE project (Rai 2017), the ICARUS project (Kocman 2018), and by USEPA (Williams et al. 2014).

1.2 The LoV-IoT sensor platform

1.2.1 Sensor testbed concept

In order to systematically evaluate performance under field conditions for the LoV-IoT sensor platform, a field testbed concept was developed. The sensor testbed concept is based on comparative measurements with official reference instrument-tation in the field for an extended time period. The purpose is to evaluate the performance of each of the tested sensors and identify biases caused by external factors under outdoor conditions. The testbed results will be used to develop postprocessing algorithms for calibration and data correction.

Within this testbed the following factors are evaluated:

- Presence of systematic offset in concentrations
- Correlation between sensor and reference
- Distribution of sensor concentrations compared to reference
- Sensor response to change in concentration compared to reference
- Drift over time
- Influence of meteorological conditions (air temperature and humidity)
- Correlation between sensors of the same type

As reference measurements were not available for other pollutants than those included in the sensor platforms (NO_2, $PM_{2.5}$ and PM_{10}) it was not possible to include cross sensitivity to other pollutants in the testbed. This is acknowledged as an important factor and may be included in further development of the testbed if possibilities arise.

To facilitate sensor evaluation in the testbed concept, a script automizing the analysis was developed in Python. The code automated and standardized data retrieval from the LoV-IoT data platform, performed a primary data post-processing, evaluated the data on the factors above, and generated a result document including all relevant figures and metrics. This enabled an automated and standardized sensor evaluation.

1.2.2 Field evaluation of the LoV-IoT platform

The sensors included in the LoV-IoT air quality sensor platforms were carefully selected and tested before field application. A detailed presentation of the selection process and the first sensor performance evaluation is presented in Deliverable 4.3 (Chapter 5 in this document). The field evaluation presented in this chapter only concerns the sensor selected for the final platform, which are presented in Table 1.

Table 1: Sensors included in the LoV-IoT air quality sensor platforms. See Deliverable 4.3 (Chapter 5) for a complete list of all evaluated sensors.

Sensor	Parameter measured
Bosch BME280	Air Temperature and Humidity
Plantower PMS5003I	Airborne particulate matter, $PM_{2.5}$ and PM_{10}
Alphasense NO2-B43F	Nitrogen Dioxide, NO_2
Insplorion LUFT-NO2	Nitrogen Dioxide, NO_2

To apply the testbed concept on the LoV-IoT air quality sensor platforms, these were initially set up at the official reference urban background station Femman in Gothenburg. It is important that the sensors are evaluated in as similar conditions as possible for the intended end use. The LoV-IoT air quality sensor platforms are primarily intended for measurement of street level air quality rather than urban background, and after initial testing in background conditions, the sensors were therefore also set up for parallel measurements at one street side reference stations. The sensors were validated using similar methods in La Florida, Santiago, Chile.

Table 2: Validation sites and reference instrumentation used for the LoV-IoT sensor platform.

Validation site	Environment	Measuring height	Instrumentation
Femman, Gothenburg, Sweden	Urban background	30 meters	TEOM1405DF, NO-NO2- NOx Teledyne 200E chemiluminescence
Korsvägen, Gothenburg, Sweden	Traffic oriented	3 meters	PALAS FIDAS NO - NO2 - NOx analyzer, ECOTech Serinus, chemiluminescence
La Florida, Santiago de Chile	Urban	3 meters	SO2 analyzer, 43i Thermo Scientific™, UV fluorescence NO - NO2 - NOx analyzer, 42i Thermo Scientific™ chemiluminescence

a)

b)

c)

Figure 1. Comparative measurements at reference stations for validation purpose at the a) Gothenburg, Femman urban background station, b) Gothenburg, Korsvägen traffic-oriented site and c) in Santiago, Chile.

As a first step, the LoV-IoT sensor platforms were mounted to measure parallel with reference instrumentation at the Femman station in Gothenburg (Figure 1a). These parallel measurements were performed during several recurring periods to allow both initial and follow up field validation under urban background conditions in varying meteorological conditions. See example in Figure 2.

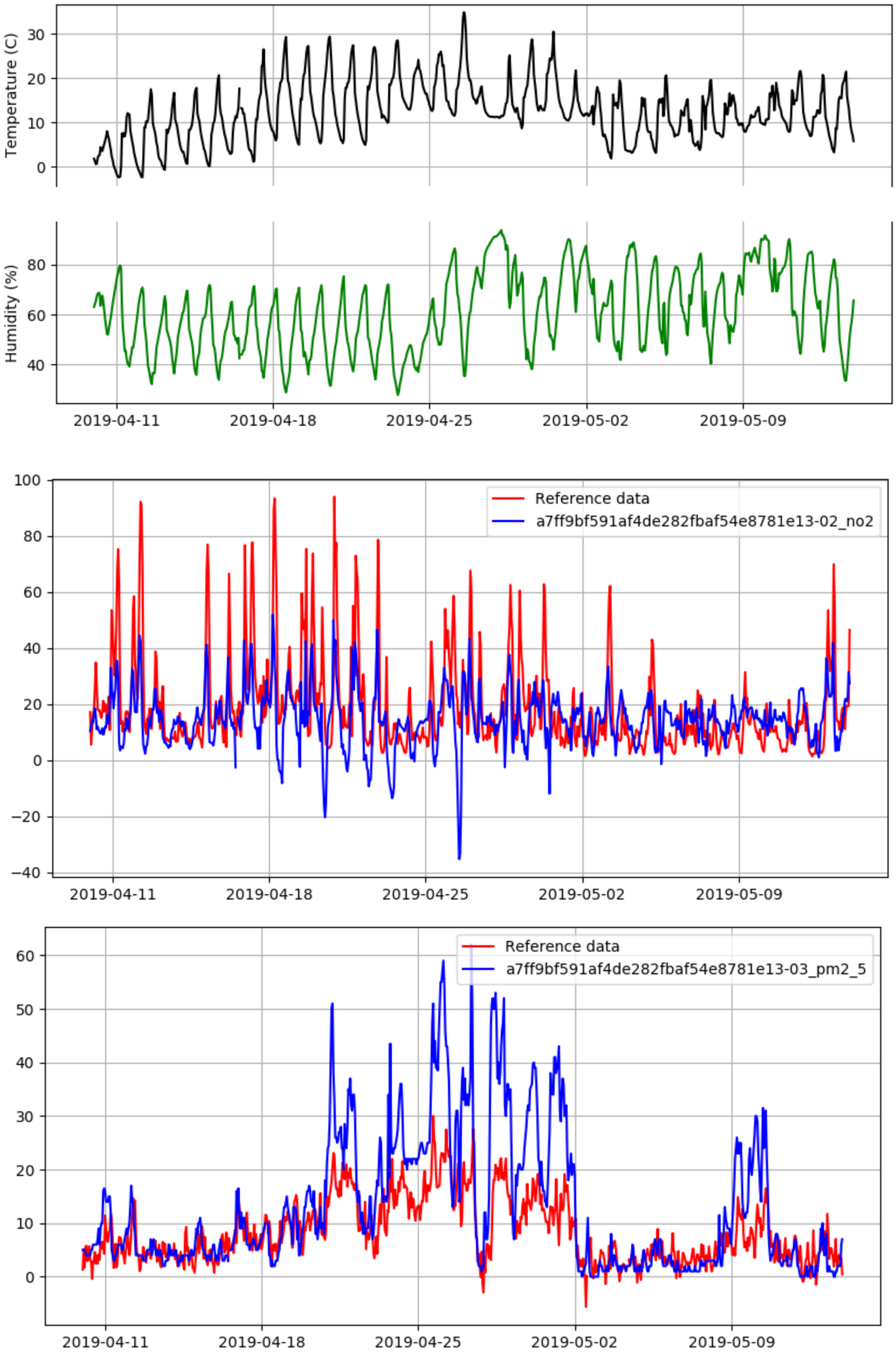


Figure 2. Example of measurements at the urban background station, showing air temperature and humidity in the top graphs, reference (Teledyne 200E Chemiluminicense) and sensor (NO2-B43F) data for NO_2 in the middle, and reference (TEOM1405DF) and sensor (PMS5003) data for $PM_{2.5}$ in the bottom graph.

When the sensor performance had undergone an initial evaluation in an urban background environment, the sensors were similarly evaluated at the Korsvägen street level site near traffic (Figure 1b). At an urban street level station, pollutant concentrations are generally higher compared to in background air and change in concentrations occur faster as the measurements are closer to the main emission source, traffic. The same testbed concept was applied to evaluate the sensor performance in a street level environment. At this site, the proximity to the main pollution source, traffic, in combination with a large ongoing infrastructure project at this site, considerably increased pollution levels and variability were expected. A similar setup and evaluation were performed at this site.

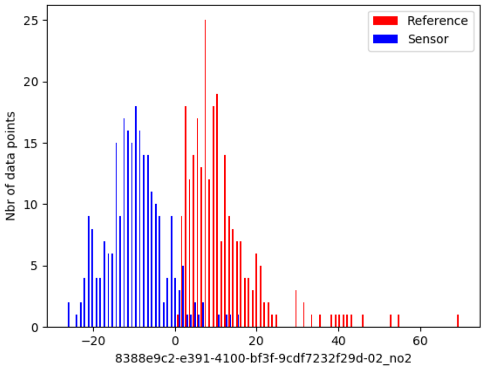
Two of the LoV-IoT air quality sensor platforms evaluated in the Gothenburg sensor testbed concept were sent to Santiago, Chile, where they were tested under Chilean conditions (Figure 1c). Three winter campaigns were carried out with gas sensors in different areas of Central Chile. The first campaign was carried out in Santiago, with focus on NO_2 sensors validation. Thereafter, the platforms were moved and distributed to an industrial urban area where each sensor was calibrated at one location and then moved to another location with similar ambient conditions to assess the adjustments. The main aim of these two last campaigns was to validate the SO_2 sensors and to create an SO_2-NO_2 sensors network.

1.2.3 Results from the sensor evaluation

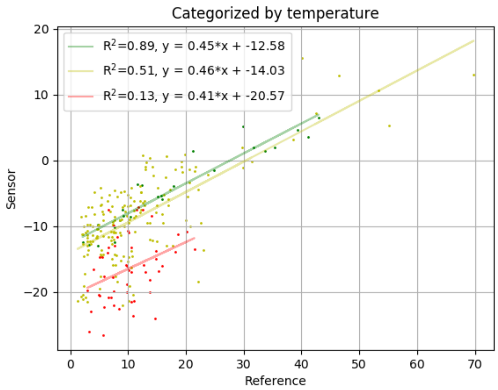
The sensor testbed concept revealed that data from the LoV-IoT air quality sensor platforms contained several biases when compared to the reference station measurements. These biases can be summed up in the following main points:

- Systematic offset in both concentration level and in distribution, was present in most sensors compared to the reference data (see example in Figure 3a).
- Correlation between sensor and reference data was affected by meteorological conditions. For NO_2, (the NO2-B43F sensor) influence was strongest for air temperature (see example in Figure 3b), while for PM (the PMS5003 sensor), relative humidity was most important.
- A significant drift over time was found in most sensors, especially for NO_2 (see example in Figure 3c).
- Correlation between sensor and reference was influenced by pollutant concentration, where for example PM sensors overestimated high concentrations and underestimated low concentrations.
- Sensors of the same type respond very similarly to changes in pollutant concentrations (see example in Figure 3d).

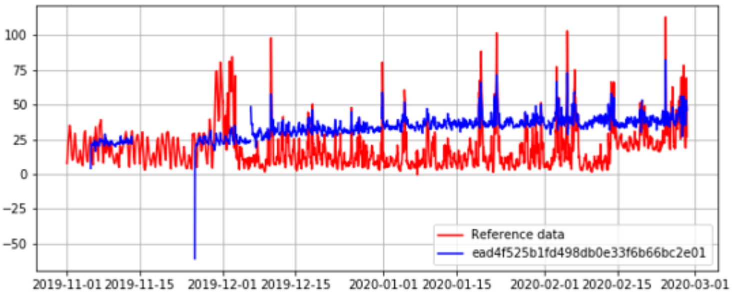
a)



b)



c)



d)

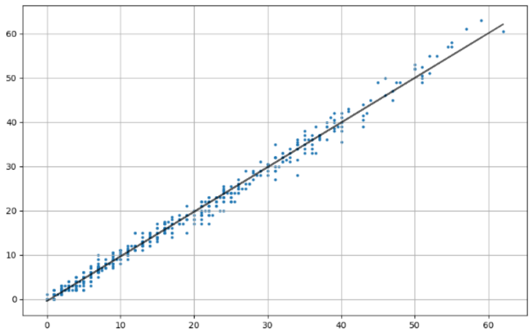


Figure 3. Examples of testbed evaluation, showing a) the offset in concentration and distribution of the data measured compared to the reference, b) the performance of the NO_2-sensor compared to the reference in different temperature intervals (green=low temperature, red=high temperature), c) drift where sensor concentrations (blue) increase over time while reference concentrations (red) do not, and d) comparison of two particle sensors (PMS5003) of the same type showing very good agreement in response between the sensors.

Evaluation of the gas sensors under Chilean conditions showed a similar performance compared to evaluations in Gothenburg. However, the influence of external factors (e.g. meteorology) creating biases in the data varied slightly, and correction algorithms, that were created based on the validation measurements in Gothenburg, were not applicable in Chile.

The SO_2 sensor was only validated in Chile. When SO_2-concentrations were low and variations limited, the sensor-performance was questionable and could not be used to accurately show SO_2-concentrations. However, when employed in the coastal industrial area of Quintero – Puchuncaví, the sensor accurately measured high peaks caused by industrial high pollution episodes, which indicate that it may be suitable for use in an early air quality alarm system.

Also included in the LoV-IoT sensor platform was the Insplorion LUFT-NO_2 sensor. This sensor has been developed during the course of the LoV-IoT project using knowledge gathered throughout the project to improve its performance. At the start of the project, the Insplorion LUFT-NO_2 had only been proven under laboratory conditions and the LoV-IoT platform has been one of the first tests of the sensor under real conditions. A lot of emphasis has been put on reaching long-term stable signals in combination with sufficient sensitivity to be able to resolve small changes in NO_2 concentration. Figure 4 shows an example of the long-term (1.5 months) behaviour of the Insplorion sensor in a real environment, as well as an example of the response of the sensor to predefined concentrations of NO_2 in a simulated environment.

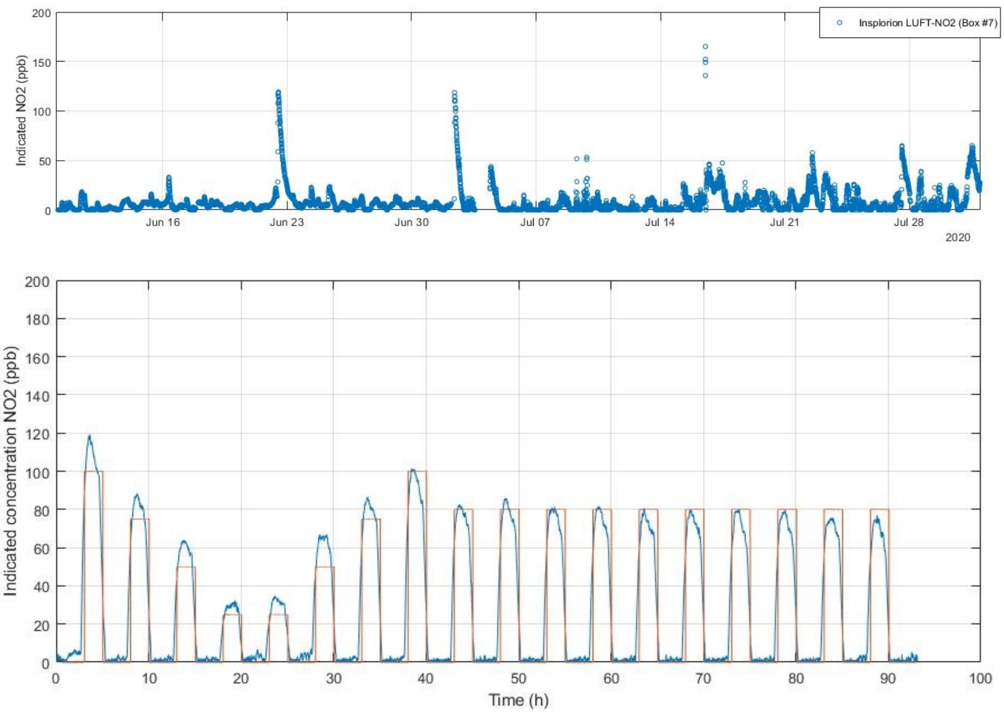


Figure 4. Behavior of the Insplorion LUFT-NO2 sensor during a field test (top) and during controlled conditions at predefined concentrations of NO_2 in a laboratory test (bottom).

1.2.4 Diagnostic tool for data post-processing

The sensor evaluation showed that sensor performance information given by the manufacturer did not apply in outdoor conditions. A clear need was identified for calibration and post processing of the sensor data in order to remove biases and increase data quality. As real time data is needed in this study, the post-processing was automated using a diagnostic tool where the input from each sensor is instantly processed in order to generate reliable data in real time.

Individual sensor post-processing algorithms were therefore developed based on the comparative measurements with reference instrumentations. The algorithms were developed using machine learning techniques. Several machine learning techniques were evaluated, and the results indicate that an MLP regressor (multi-layer perceptron) was best suited for correcting of the sensor values. The regressor was trained on sensor data, temperature and relative humidity, and used measurements from reference instruments as objective function. We found that the model performed best when the dataset was divided into three different temperature categories, see Figure 5.

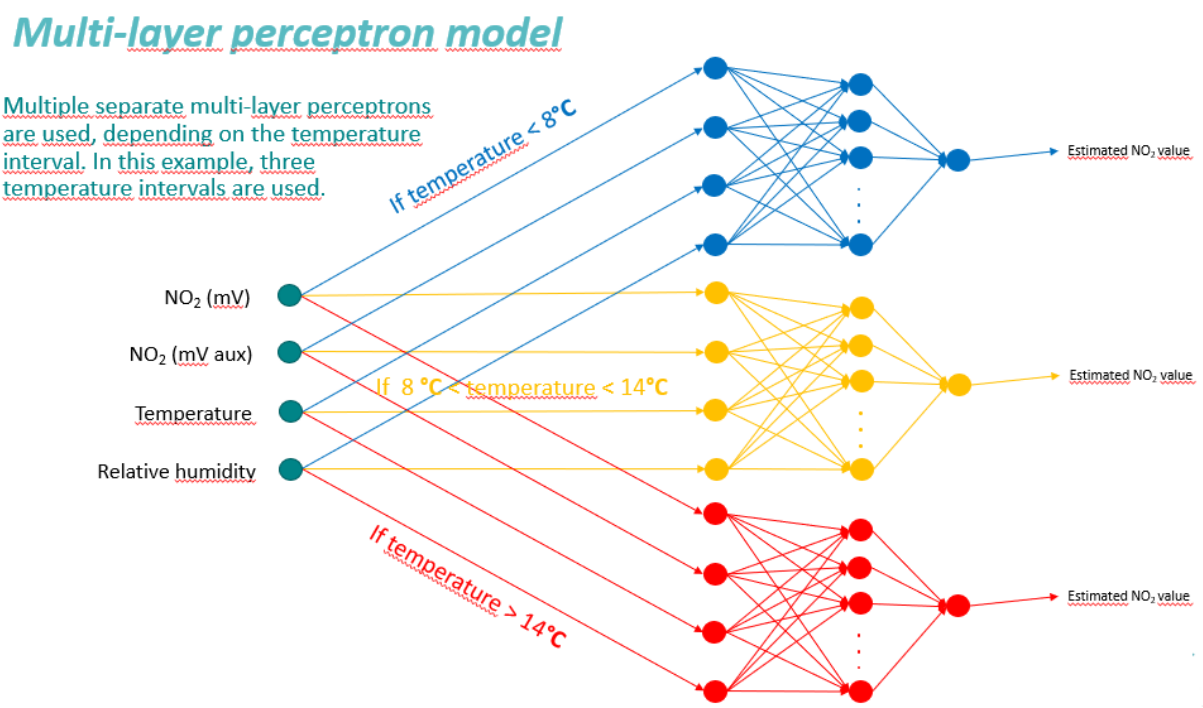


Figure 5. Layout of the MLP-regressor used for data correction.

To obtain the relevant information for development of post processing algo-rithms, each sensor is installed to measure parallel to a reference instrument for a minimum period of one month. The collected data is divided into two parts – a period covering 75 percent of the total validation measurement period is used as training data for the post processing algorithm, while the remaining 25 percent is used to evaluate the performance of the algorithm (Figure 6). By evaluating the algorithm performance on data that has been left out of training, it is tested how well the algorithm generalizes.

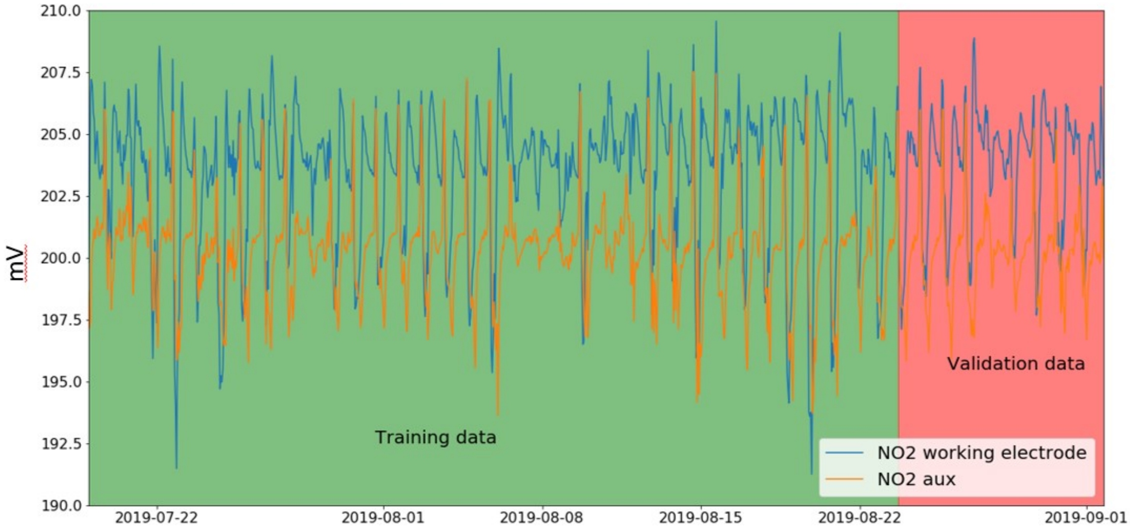


Figure 6. Example of how 75 percent of the validation period (green) is used for training of the correction model, and 25 percent is used for model performance evaluation. Image from our Chilean colleagues at CMM.

Although sensors of the same type generally responded similarly to a change in pollutant concentrations, the remaining individual characteristics of each sensor reduced the effectiveness of a general algorithm applied to all sensors.

A regressor trained on data from one sensor may thus not perform as well when applied to another sensor. The method developed in the LoV-IoT project does not require any individual modifications but to maintain high quality corrections, regressors corresponding to individual sensors need to be trained separately to optimize the effect.

Sensor performance varies with meteorological conditions, and it is therefore vital that the period of comparative measurements used for the development of post processing correction algorithms is representative for the conditions intended for use. It may be necessary to repeat the comparative measurements during periods with different meteorological conditions to adjust the post processing algorithms to seasonal changes.

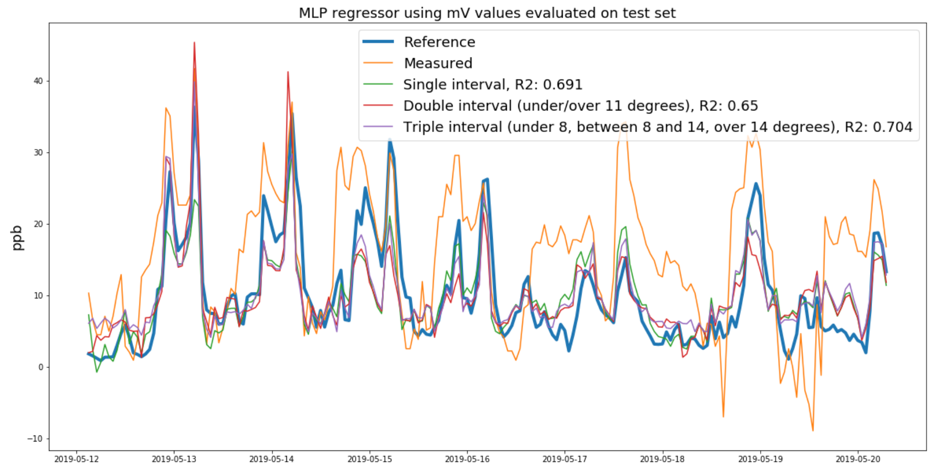


Figure 7. Example of the effect of the post processing algorithms applied to the sensor data for NO_2. The graph shows the evaluation period (the 25 percent where the model performance is tested, red period in Figure 6), with data from reference (blue), sensor data without correction (orange), sensor data corrected using all temperatures (green), data temperatures divided into two intervals (red) and temperature divided into three intervals (purple).

With these post processing algorithms, sensor performance in comparison with reference data generally increased. The resulting R^2 values after post processing varied but generally increased and reached up to between 0.7 and 0.8. High R^2 values occurred when training was performed in similar conditions (temperature, relative humidity and pollution levels) as where the R^2 was evaluated. However, this also shows that a considerable uncertainty remains in the data, with unknown factors causing between 20 and 30 percent of the variation in the data, when the post processing is performing at its best. This is important to keep in mind and should be carefully considered when using these sensors for air quality measurements.

The necessity of applying correctly developed post-processing algorithms is exemplified in Figure 8. In this figure, the sensor data (blue) is collected at ground level in an infrastructure development site and compared to a nearby rooftop reference station (red). This reference station is located approximately 30 meters above ground level. As most emissions occur at ground level, concentrations are likely to be higher and show more variability in street level measurements (i.e. the LoV-IoT sensor platforms) while the increased distance from the source at the rooftop station lowers concentrations and variability in the data. In the figure, raw data (top row) show some agreement with the reference station and follows the expected pattern with higher concentrations and larger variability. In the bottom row, post-processing algorithms developed in winter conditions are applied to the same sensor data, which is collected in summer conditions. This produced *"corrected"* sensor data that showed the opposite pattern, with lower concentrations and much smaller variability at ground level. This is likely not accurate and applying these incorrect post-processing algorithms likely decreased the data quality and removed important information.

Diagram showing sensor data described in the text for figure 8.This clearly exemplifies that it is critical that post-processing algorithms are developed based on measurements in representative conditions and environment.

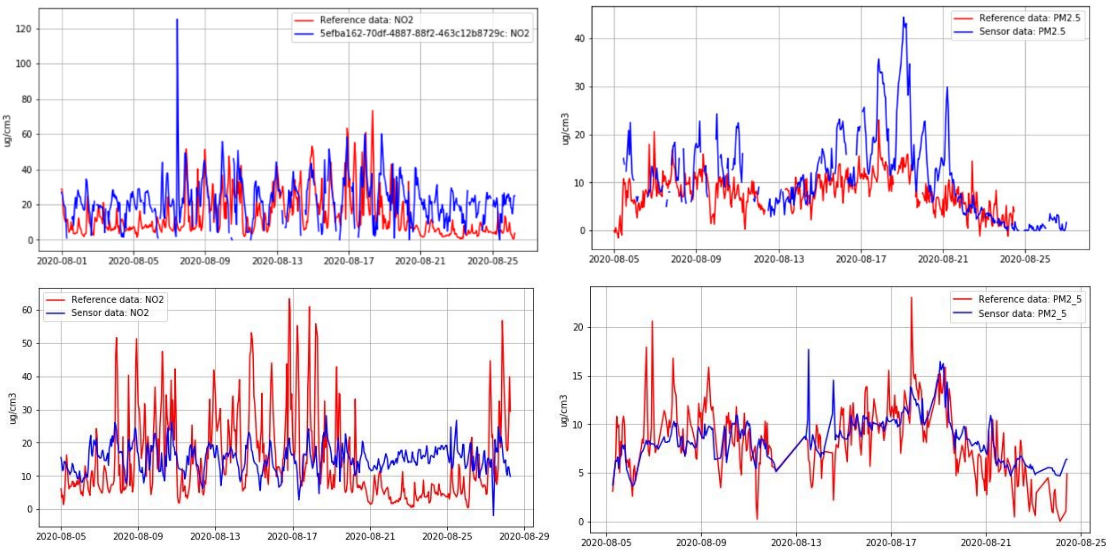


Figure 8. Time series showing raw sensor data (top row) and sensor data post-processed with incorrectly developed algorithms NO_2 (left) and $PM_{2.5}$ (right) measured at the Central station site in Gothenburg. Data is compared with reference data (red) from the nearby rooftop reference station Femman. Please note the differences in scales in the graphs.

As mentioned above, the models generated based on validation measurements in Gothenburg were not applicable when sensors were applied in Chilean conditions. The Gothenburg model performance could not be used to increase the performance in Chile. New correction algorithms suitable to Chilean conditions were therefore made using a multiple linear regression model, in which the variables of sensor temperature and relative humidity were incorporated. Also, in these conditions it was found that dividing the data obtained in each campaign into 3 sections, according to temperature and voltage for NO_2 and SO_2 sensors respectively, to comply with the assumptions of the model.

The mutual comparison of the sensors indicates that the individual operation depends on its intrinsic sensitivity to environmental factors. The segmentation methodology allowed the sensor response to be adjusted over a wide range of ambient temperature and humidity variability (NO_2: R^2> 0.6 - SO_2: R^2 > 0.98). The performance of NO_2 sensors get worse when they move from an urban area (R^2> 0.8; bias <15 percent) to an urban-industrial one (R^2> 0.6; bias> 30 percent). The SO_2 sensors were only evaluated in Quintero, where their adjustment was greater than 0.9; because the high environmental concentrations agreed with the high measured voltages.

1.2.5 Suitable applications for low cost air quality sensors

The work in the LoV-IoT project has shown that the low-cost air quality sensor platforms can indeed be very useful and have many suitable applications. However, it is important to take the performance limitations and maintenance, calibration and post-processing needs into account when integrating LCS platforms in air quality monitoring. Experiences from the LoV-IoT project can be summed up in the following conclusions regarding suitable applications:

- **For citizen science and communication purposes**
  Due to their low cost, these sensors are suitable for incorporation in outreach activities and used for citizen science. The citizens can be allowed to build and experiment with the sensors and there is room for trial and error even in a limited budget. However, it is still important to plan in advance how the sensors will be used and what the use should add and contribute to. It is also important to make sure that the participants are aware of limitations in data quality and applications.
- **For complementary measurements**
  Due to the limitations in the ability to correctly measure absolute pollutant concentrations, LCS technology should not replace reference measurements but only be used to complement these and to extend station density. Thus, since LCSs of the same type generally react similarly to external factors, such as change in meteorology, a sensor measuring parallel to the reference instrumentation can thus be used to identify and calibrate for such biases in the whole LCS network.
- **Measurements with limited spatial extent**
  Due to the sensitivity to changes in meteorology, LCS networks should only be applied within a spatially limited area, where the meteorological conditions do not differ to the extent that a different bias is created within the sensors in the network.
- **Measurements with limited temporal extent**
  Due to the tendency for drift in sensor performance with time, LCS networks should only be applied within a time period limited to well within the expected life span of the sensors. It is also recommended to identify and calibrate for drift for all studies intended for longer time periods.
- **For identifying patterns**
  Since sensors of the same type react similarly to changes in both the intended pollutant and the biases, these sensors are well suited for assessing patterns and identifying deviations from these patterns within a smaller geographic area.
- **For initial rough measurement and indication**
  In situations where a rough indication of rapid change in air quality is needed, LCS networks may be suitable for an early warning system or as a tool for a rapid first assessment. Such situations could for example be during a fire or during sudden major pollution release from, for example, industrial processes. This requires a good understanding of the sensor’s response to change, and generally follow-up measurements with high quality instrumentation.

In practice, this means that LCS networks are suitable for assessing the changes in air pollutant concentrations around places of interest, in studies with limited spatial and temporal extent. Such an application could, for example, be assessing the detailed variations in pollutant concentrations around a school in order to identify the most polluted microenvironment, perhaps to assess where mitigation efforts such as barriers between pollution sources and exposure locations should be focused. As with all measurements it is vital that the location and orientation of sensors and sensors inlets/filters are carefully selected to represent the intended area and to avoid biases.

It could also be an increased air quality monitoring network around large infrastructure projects. At these sites, emissions are typically closely dependent on activity that can cause large variations in air quality over short distances. A denser measurement network around these sites may be very useful for adequate control of air quality as well as for the assessment of appropriate mitigation measures.

As previously stressed, it is vital that the proper maintenance and post processing is applied when using LCS technology. It is important to remember that using LCS technology does not limit the need for maintenance and calibration of the sensor technology. The sensors will need continuous calibration, preferably through comparative measurements before and after use in the field. Just like any sensor technology, the LCS may break down and malfunction, and thus require maintenance, repair or replacement. While the replacement cost may be low for LCSs, the need for validation and calibration remains for each replacement unit. If more sensors are used, the need for maintenance will increase. This is important to take into consideration when planning measurement campaigns using a large number of sensors.

2 Sensor platform developed from TRL 5 to TRL 6

The goal was to further the technology readiness level (TRL) of the LoV-IoT air quality sensor platforms from stage 5 to 6. The criteria for achieving TRL 6 is that the technology is demonstrated in a relevant environment, i.e. a prototype has been tested and shown adequate performance in the environment in which it is intended to be used.

This goal has been reached as the sensor platforms have been tested and shown adequate performance in the environment where it is intended to be used in the following studies.

2.1 Korsvägen, Gothenburg

The LoV-IoT sensor platforms were tested at the major infrastructure project at Korsvägen, Gothenburg, where they were mounted to measure parallel to a reference station (Figure 9).

Figure 9. LoV-IoT air quality sensor platforms evaluated at the Korsvägen infrastructure project in Gothenburg.

Presented below are data from one of the LoV-IoT sensor platforms as well as the reference instrumentation measured during the parallel measurements at a reference station. Data from the sensors are post processed in the diagnostic platform using algorithms based on comparative measurements at the same site according to the method presented in chapter 1.2.4. The resulting data show good agreement with reference data from the parallel measurements at the reference station, see example in Figure 10.

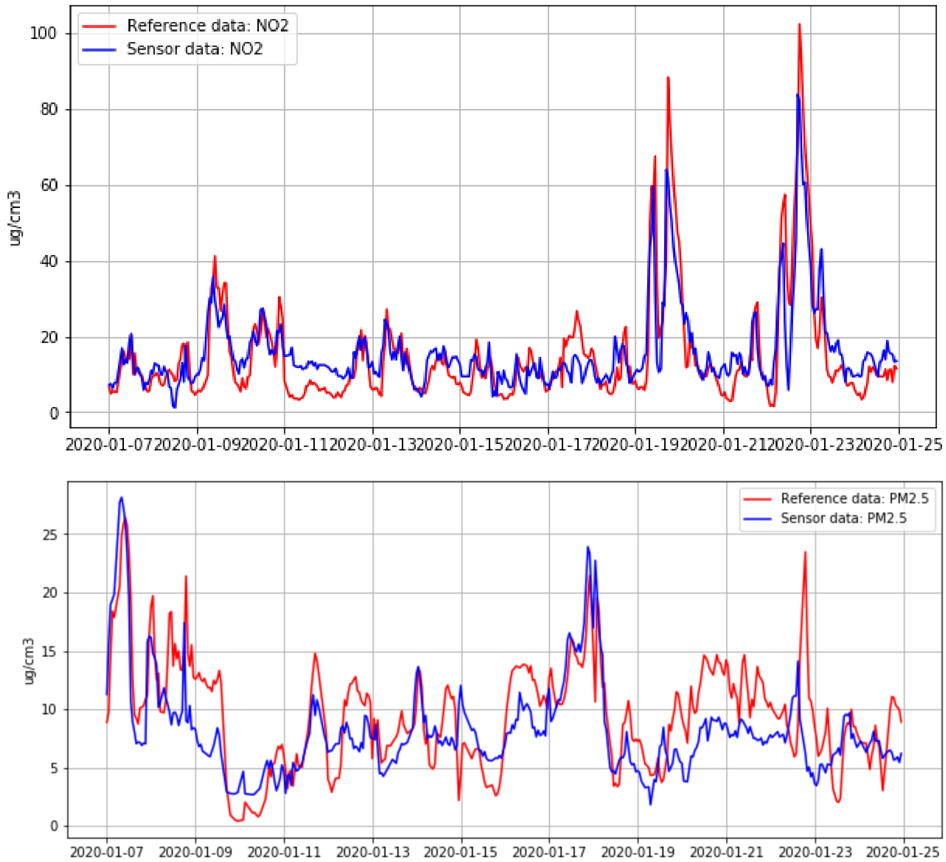


Figure 10. Time series showing reference (red) and sensor (blue) data of NO_2 (top) and $PM_{2.5}$ (bottom) measured at the Korsvägen site in Gothenburg.

2.2 The Central station, Gothenburg

The sensor platforms were set up at the site of an additional major infrastructure project in Gothenburg, located near the central train station (Figure 11).

Figure 11. Measurements at the Central station infrastructure project site in Gothenburg. Photos showing the sensor platforms in view towards (from left to right) the south, east, and west.

At this site, the platforms were not measuring in parallel with a reference station because none are available. The closest reference station is the roof top urban background station that were used for the initial tests of the platforms. This reference station is located approximately 30 meters above ground level, while the LoV-IoT sensor platforms are mounted at approximately 3 meters above ground. Since most emissions occur at ground level, concentrations are likely to be higher and show more variability in street level measurements (i.e. the LoV-IoT sensor platforms) while the increased distance from the source at the rooftop station lowers concentrations and variability in the data.

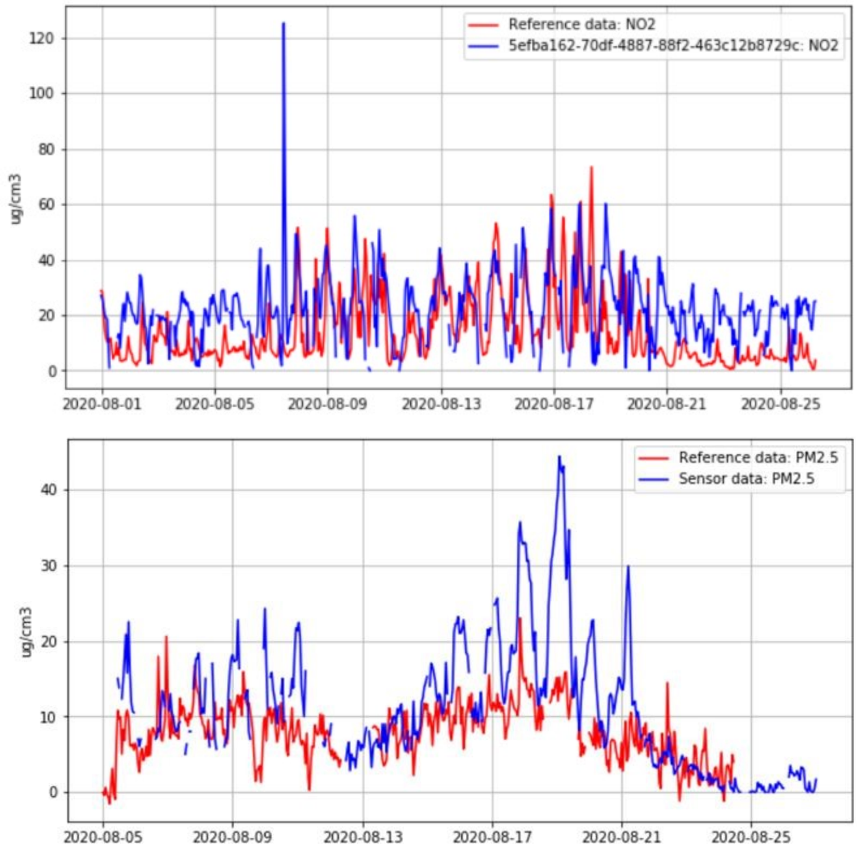


Figure 12. Time series showing data from the sensor (blue) and the nearby rooftop urban background station at Femman (red), of NO_2 (top) and $PM_{2.5}$ (bottom).

Figure 12 present results from one of the LoV-IoT sensor platforms at the Central station site together with reference data from nearby rooftop urban background station at Femman. No parallel reference measurements were available for development of post processing algorithms at this site. Results presented in figure 12 therefore presents raw data. The raw data display shows some agreement with the rooftop background station, but in order to obtain high quality data from this site, application of post-processing algorithms developed based on a period of parallel measurements during representative conditions would be required. This was however not possible within the frame of this project. More information can be found on this in Deliverable 4.1, Chapter 1.2.4 in this report.

2.3 Uppsala

The City of Uppsala is currently (2017–2019) facing problems with high levels of nitrogen dioxide (NO_2) exposing inhabitants (as well as pedestrians and bikers) in the city centre. This evidence comes from a (the only one) stationary air pollution measuring devise, placed at one of the busiest streets in Uppsala – Kungsgatan. There is also a recent history of high levels of particles (PM_{10}), however currently in acceptable levels.

In Sweden air pollution levels are considered high when the Swedish environmental quality standard for air pollution (MKN, abbreviation for miljökvalitetsnormer) is exceeded. With the exception of annual averages, there are quality standards for daily mean value and mean value per hour. These are levels that must be achieved according to Swedish law. It is usually most difficult to achieve MKN for daily mean value and per hour.

Information of air pollution levels indicating if MKN is reached can also be found in calculated air pollution maps based on traffic flows, these are made every five years. When the MKN is exceeded the local administration, in this case Uppsala municipality, is required to report actions that will be taken through an action plan (to the government). Uppsala has had an action plan for air pollution since 2006, especially for NO_2 and PM_{10}.

Figure 13. The LoV-IoT sensor platforms installed at Kungsgatan in Uppsala.

An LoV-IoT sensor platform has been installed at Kungsgatan (where high levels of NO_2 are known) on a balcony, relatively close to the street (Figure 13). The location is about 500 meters from the stationary reference air pollution station placed at Kungsgatan, close to the Central station. This sensor location was suggested due to the possibility of comparing the results with the reference measurements, which will provide comparative measurements for the development of post processing algorithms and may provide an indication of the magnitude of air pollution along Kungsgatan. Figure 14 shows preliminary data of NO_2 and $PM_{2.5}$ from the sensor platform. Another sensor platform will be placed near the narrow street Övre Slottsgatan, where the air pollution map indicates that the MKN is exceeded for NO_2.

Figure 14. Preliminary data from measurements at Kungsgatan in Uppsala. No post processing algorithms are applied.

2.4 Chile

A second field application was carried out together with Centro Mario Molina (CMM) in Santiago, Chile. The LoV-IoT sensor platforms has so far been tested in three different settings in Santiago and Quintero; an urban and industrial area. The monitoring platform for Chile was adapted to also include an SO_2 sensor, as SO_2 concentrations occasionally exceed harmful levels in certain Chilean environments. Sensor performance under Chilean conditions has shown that the sensor platform can provide useful information if used as a complement to the current reference station infrastructure (Figure 15). Initial assessment also shows great potential of using SO_2 sensors in an early warning system for when rapid increases in SO_2 concentrations occur.

Figure 15. Time series of 1-hour averages of the model output (SO_2 sensors) and reference gas concentrations, in Quintero Monitoring Station.

Figure 16 shows the platform in the station of Valle Alegre in Valparaiso Region, Chile. This station is a rural industrial background station. Figure 17 shows the sensor platform in Ventanas, Valparaiso Region, Chile. This station is an urban industrial station.

Figure 16. Platform in Valle Alegre, Valparaíso Region, Chile.

Figure 17. Platform in Ventanas, Valparaiso Region, Chile.

Raw data as well as post processed data and reference data from the validation site at Ventanas, Chile, is presented in Figure 18. The post-processed data show a good agreement with the reference data.

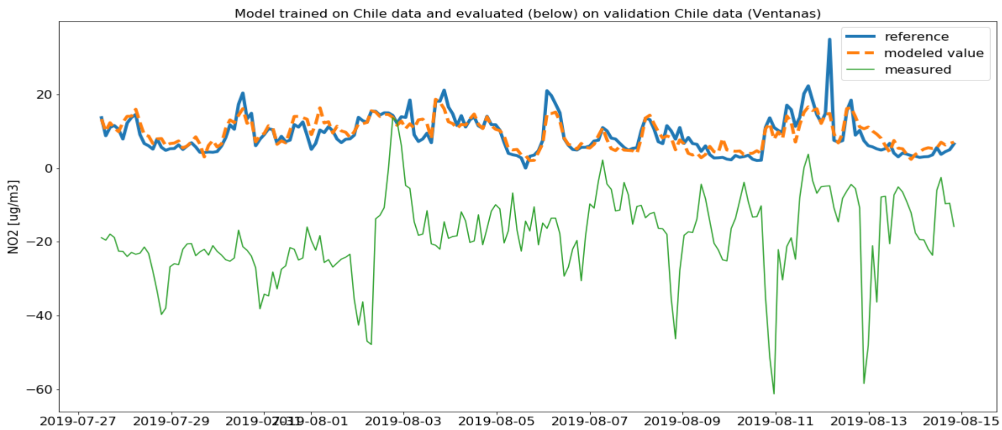


Figure 18. NO_2 concentrations measured at Ventanas. Raw data presented in green, reference data in blue and post-processed data as orange dashed line.

3 Operations and availability

The data collection solution, see Figure 19, consists of several different parts ranging all the way from the physical sensors, through the different parts of the infrastructure, up to the storage and analytics platform. This section describes the collection, transfer and interim storage of sensor data.

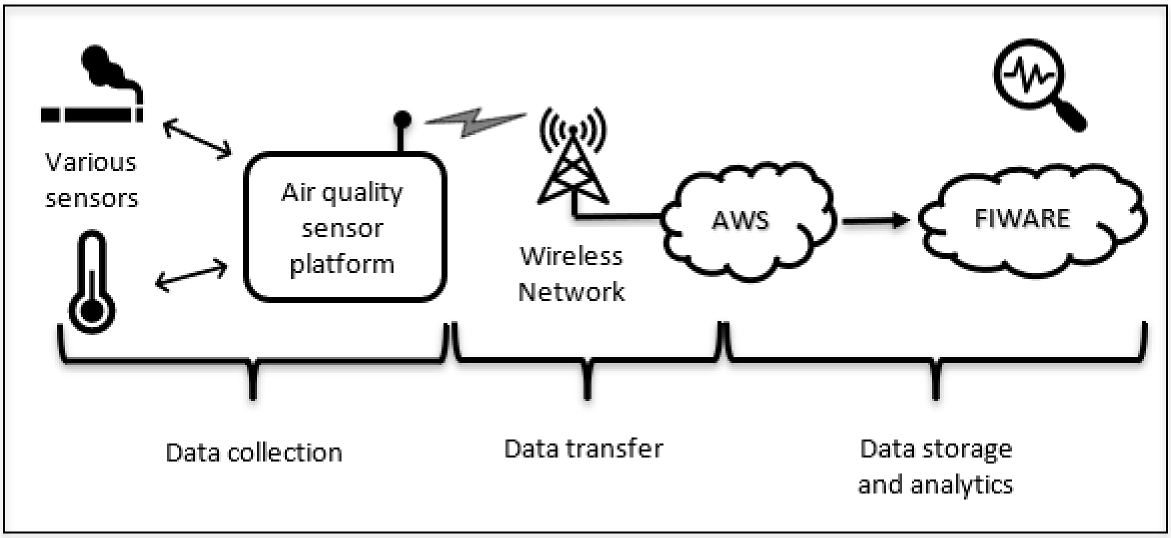


Figure 19. Communication solution overview.

3.1 Data collection

Data collection is done by an air quality sensor platform with various sensors connected to it, primarily measuring nitrogen dioxide (NO_2) and particulate matter (PM_{10}, $PM_{2.5}$). Other sensors, which are measuring air temperature, air pressure, relative humidity and noise, are also included.

3.1.1 Air quality unit hardware

Since the purpose with the LoV-IoT project was to evaluate the use of LCSs and not to develop commercial products, the choice of hardware for the sensor platform was primarily driven by the need for flexibility and high development speed. A decision was made early to go for a development board since they typically offer a wide range of communication interfaces and I/O options.

Table 3: Criteria for a suitable hardware

Selection criteria	
Physical surroundings	The unit has to be placed outdoors and inside an additional larger IP65 or higher environmental protection box also housing a power supply, sensors, antennas, etc. There is also need for semi-open part in the box, where sensors must have contact with surrounding air and environment.
Power requirements	The complete unit with sensors would be too energy hungry to be run on battery power, therefore an external, fixed power source was required. It also needed to be low voltage, thus avoiding certified technicians to be called on every mounting. No reserve power supply was required in case of main power supply failure, but such can be added in the future.
Sensor interface	Since different sensors were to be evaluated throughout the project, several analog and digital sensor interfaces were required. See section Sensor interfaces.
Wireless communication	Several alternatives were considered, like Wi-Fi, 3G/LTE, NB-IoT and LoRA, but since every air quality unit would have a handful of sensors and send a lot of data, the decision was to use 3G/LTE which usually offers data plans with enough data and also have good outdoor coverage. GPS receivers are also good to have, so measuring boxes can also be used in mobile measurement.
Processor and memory capacity requirements	In order to not spend too much time adopting to hardware limitations, the decision was to use powerful microcontrollers with a lot of memory (both flash and RAM).
Security	Hardware needed to be powerful enough to handle the required security, such as Transport Layer Security (TLS).
Flexibility	Since requirements and needs are likely to change over time of the project, a selected hardware should ideally be part of a family of devices so that a change could easily be made if required.
Development speed	In order to be able to reuse standard libraries and existing functionality, a well distributed operating system with a large community was the preferred choice.
Support possibilities	Adequate support possibilities were crucial for good functionality. If the development board and the chosen operating system were widely used it would be easier to get support, and discussion forums would be available.

After careful market research, based on the above bullet points, the decision was to use the C030 evaluation board from U-blox (https://www.u-blox.com/en) together with Mbed OS (https://os.mbed.com/) as an operating system since it offered good options for connecting sensors as well as alternative communi-cation methods. Sensors can be connected using various interfaces; Analog-to-Digital Converter (ADC), Inter-Integrated Circuit (I2C), Serial Peripheral Interface (SPI) and RS-485 that allow to evaluate many different types of sensors. The selected U-blox board offers Ethernet and Cellular connectivity as well as GPS, but due to the large range of boards with support for Mbed OS a migration to a different board with other communication options is quite simple.

The C030-U201 Application board offers:

- STM32F437VG Cortex-M4 ARM host MCU with 1024 kB Flash, 256 kB SRAM
- HSPA/GSM cellular network
- GPS/GNSS (Global Navigation Satellite Systems) functionality
- SD card socket for file storage
- Extension:
    - Arduino™ Uno R3 compatible interface
    - 6 analog capable inputs
    - 8 PWM capable outputs
    - 22 GPIOs
    - 1 x SPI
    - 1 x I2C
    - 1 x UART with HW flow control option (RTS, CTS)

3.1.2 Sensor interfaces

Sensors used in the project required a range of different interfaces:

- **UART**
  Universal asynchronous receiver-transmitter (UART) is a serial data interface used to communicate with other devices that include their own processing unit.
- **SPI**
  Serial Peripheral Interface (SPI) is a synchronous serial communication interface specification used for short-distance communication, primarily in embedded systems.
- **I^2C**
  Inter-Integrated Circuit (I^2C) is a short-distance synchronous interface.
- **Analog inputs**
  An input for sensors that only give a voltage level that corresponds to the value.

3.1.3 Operating system

Mbed OS was chosen as the operating system and it is a free, open-source embedded operating system designed specifically for "things" in the Internet of Things. It comes with a lot of functionality out of the box including a wide range of connectivity options like cellular networks and LoRa LPWAN.

3.1.4 Sensor data

Each sensor is typically sampled by the sensor platform every second and an average together with standard deviation is calculated per minute. Every minute, data from all sensors are aggregated into a JavaScript Object Notation (JSON) message and sent to the backend over MQTT (http://mqtt.org/). If communication is unstable, the device will queue the data messages for later delivery in order to minimize potential loss of data.

The JSON structure consists of 2 parts where part 1 describes the physical device with a unique device id, a device type and current GPS position:


```
"deviceid":"8388e9c2-e391-4100-bf3f-9cdf7232f29d",
"devicetype":"UBLOX_C030_U201",
"location":{
  "latitude":"-32.74855",
  "longitude":"-71.47478",
  "altitude":"-0.5"
}
```


The second part is a variable list of sensor readings containing values for all sensors connected to that specific sensor platform. Each sensor reading is built up with sensor information, a time stamp and the relevant data values for that specific sensor. All timestamps are in Coordinated Universal Time (UTC) and each data value is self-describing with id, value, standard deviation, value type and unit.

Below is an example for the BME280 sensor which measures temperature, pressure and humidity.


```
"sensor":{
  "sensorid":"8388e9c2-e391-4100-bf3f-9cdf7232f29d-04",
  "sensortype":{
    "id":"04",
    "name":"BME280"
  }
},
"timestamp":"2020-06-01T06:59:12Z",
"sensordatavalues":[
  {
    "id":"val-1",
    "value":7.97,
    "stddev":0.01,
    "valuetype":"temperature",
    "unit":"degC"
  },
  {
    "id":"val-2",
    "value":1022.49,
    "stddev":0.04,
```

```
        "valuetype":"pressure",
        "unit":"hPa"
      },
      {
        "id":"val-3",
        "value":89.7,
        "stddev":0.01,
        "valuetype":"humidity",
         "unit":"%"
      }
  ]
```


3.2 Data transfer

Each air quality sensor platform connects to internet using its built in 3G/4G modem enabled by a data traffic subscription from a global mobile operator. The internet connection is used to:

- Send sensor data to the interim data storage in Amazon Web Services (AWS)
  - Send log files to AWS
  - Periodically update the Real Time Clock (RTC) using network Time Protocol (NTP)
  - Remote device management including firmware upgrade

Once successfully connected to the internet over the mobile network, the sensor platform will connect to the AWS IoT Core using mutual Transport Layer Security (TLS) with the locally stored client certificate. Only IoT devices with valid certificates can connect to the interim data storage. When the connection is established both ends are authenticated and the communication is securely encrypted.

In order to send and receive messages between sensor platform and AWS, MQTT is used. MQTT is a lightweight protocol designed specifically for machine to machine communication and well suited for sensor applications. The protocol is based on publish and subscribe to specific topics and the air quality sensor platform only uses 3 MQTT topics:

- lov-iot/{uuid}/command – Commands from AWS backend to IoT devices
- lov-iot/{uuid}/device-data – Sensor data from IoT devices to AWS backend
- lov-iot/{uuid}/log – Log files from IoT devices to AWS backend

Each sensor platform is identified by a Universally Unique Identifier (UUID) which is also part of the topic names.

3.3 Interim data storage – Amazon Web Services (AWS)

All connected devices connect to the AWS IoT Core and publish sensor data. Sensor data received from connected device is forwarded to the Fiware broker and stored in AWS.

At the beginning of the project was the development of the connected platform before the Fiware integration and a backend was needed. An AWS solution was implemented to store and periodically export sensor data. When the project was ready to integrate with Fiware a step was added to forward data to it in addition to storing data in AWS. Received sensor data is also fed to an analytics engine (AWS IoT Analytics) but no analytics is currently performed on the data.

Fiware connects as an MQTT client to the AWS IoT broker and subscribes to a specific MQTT topic used. This client may only subscribe to that topic and attempts to subscribe to other topics or publish on any topic results in a disconnection from the broker.

When data is received on an MQTT topic in AWS IoT Core one or more actions may be triggered based a set of rules. The following topics are used to trigger rules:

- lov-iot/{uuid}/log
- lov-iot/{uuid}/device-data
- lov-iot/egress/data-stream - egress data stream to Fiware

The following rules are used:

- SaveDeviceLogInDynamoDB – saves messages received on the log topic to the DynamoDB table 'lov-iot-raw-log'
- FiwareIntegrationRule – republishes messages received on the sensor data topic to Fiware
- AnalyticsRule – sends messages received on the sensor data topic to AWS IoT Analytics
- SaveDeviceDataInDynamoDB – saves messages received on the sensor data topic to the DynamoDB table 'lov-iot-raw-device-data'

3.4 Device management

One major challenge in IoT solutions is the management of the physical IoT devices distributed over a large geographical area. When scaled up to hundreds, thousands and perhaps tens of thousands of devices the need for easy installation and remote management is crucial. Since the field trials in this project included only tens of devices, the focus was on easy installation, remote management and remote firmware upgrade in order to minimize the requirement to physically go to the sensor platforms for maintenance.

3.4.1 Device provisioning

Provisioning/production of new sensor platforms is done with Python scripts that perform several steps to properly prepare the device to be a sensor platform connected to AWS IoT Core:

1. A UUID is created to uniquely identify the air quality sensor platform during its lifetime
2. Several configuration files are created using the UUID:
   - Sensor configuration
   - GPS configuration
   - Log level configuration
3. The sensor platform is registered in AWS IoT Core and a client certificate for secure connections is created and retrieved

After completing the device provisioning script, all files are copied to a Secure Digital (SD) card along with the latest firmware. The SD card is then mounted on the C030-U201 application board installed inside the sensor platform. After power-up the sensor platform will connect to the AWS IoT Core over the cellular network and continuously deliver sensor data.

3.4.2 Device Logging

The air quality sensor platform sends log data to the AWS backend to support troubleshooting and all logs are stored in AWS DynamoDB. Several different log levels are supported to balance the need of logs for troubleshooting and the need to not drive cost by sending too much data:

Table 4: Log data sent from the air quality sensor platform to the AWS backend

Severity	Level	Description
LOG_OFF	0	no logs at all
LOG_ERR	1	error conditions
LOG_WARNING	2	warning conditions
LOG_INFO	3	informational
LOG_DEBUG	4	debug-level messages

Under normal conditions the level is typically set to LOG_ERR or LOG_WARN to keep the amount of logs down. However, during troubleshooting when more logs are required. The log level as described in the next section.

3.4.3 Remote device management and firmware upgrade

In order to minimize the need to physically go to the sensor platforms if issues occur, a set of remote commands is supported:

- **reset** – will cause the firmware to restart
- **setLog** – changes the log level

- **download** – triggers a remote update of the firmware. Remote firmware upgrade is used whenever new updated versions of the device firmware exists and need to be deployed to devices in the field.
- **resetI2CSensors** – resets the I2C sensors

The commands are sent over the MQTT topic lov-iot/{uuid}/command as JSON formatted data: {"command": "reset"}

4 Sensors – selection, test, comparison and integration

Measuring air quality is usually performed with sensors for necessary pollutant concentrations – dust/particles, different gases in combination or not with additional weather station (temperature/humidity, wind directions, solar radiation, precipitation) and sometimes noise/vibrations.

High, mid and low-cost sensors of all kinds are manufactured by large and small companies that offer myriad of sensors with different sensing principles, accuracy, availability, stability, life cycle, etc. These sensors have a large number of applications – research and development, science, industry, automotive industry, medicine, public health and safety, education, etc. But the most important physical and chemical foundations and laws did not change, so usually sensors can be easily divided into a few basic groups.

Practical selection of sensors for the sensor platforms is done in several steps:

- Review the currently available sensors and available tests and comparisons
- Check the sensors manufacturer's data sheets and application notes, availability and price (it can be low cost commercially available sensors, but it can also be new and R&D sensors, where price is not so important)
- Buy sensors or sensor evaluation boards and test them indoors in the laboratory and outdoors next to calibrated reference stations for extensive time and different weather evaluations and comparisons
- Plan and do integration of different sensors and chosen communication and mechanical platform

The focus of the selection was on the set of requirements/criteria described in Table 5.

Table 5: Sensor selection criteria and questions

Selection criteria	Sensor selection questions
Basic properties	**Sensing technology?** Is this a well-proven manufacturer and technology (if description is available), how sensitive is the sensor to the intended measured parameter? Cross-sensitivity? How often measurement needs to be performed – seconds, minutes, hours, days? Any pre-calibration needed? **Sensing requirement to place and way to integrate?** Operating temperature and humidity range, maximum operating altitude, level of noise and vibration? Need for compressed air or vacuum, different gases, defined airflow? Protection from sunlight, particles, water, etc. **Packaging?** Is it the sensor only, is it packaged or does it need a special package? Additional protection against the elements outdoors?

	Sensor electronics? Is there amplifiers, filtering, analog to digital converter, power conditioning? Is sensor electronics delivered with a sensor or is it available as separate board? **Communication possibilities?** Available interfaces – analog (voltage, impedance, DC resistance, current, modulation) and/or digital (serial - I2C, SPI, UART or parallel). GPIO needed in total to control and log data from the sensor. For more sophisticated sensors cable or wireless communication to Intranet/Internet-based database/postprocessing – via broadband or narrowband radio communication. Examples are GSM 2/3/4/5G, LoRa, ZigBee, Bluetooth, WiFi, Sattelite, etc. **Position, logging, display and configuration options?** For more expensive, complete and sophisticated sensors – GPS position available, local logging on internal or external memory. Display and feedback lights, sounds, transducers? Configuration buttons and keyboard? **Size and weight?** Physical size of sensor, or sensor with sensor board? **Power requirements?** Battery or fixed power source needed? Requirements for standard or low noise level? **EMC/ESD protection?** Method and place of installation, protection against external EMC/ESD sources and accidents. **Durability?** How sensitive to power fluctuations, accidental drops, hits, overload, dust, water, etc. **Price and availability?** Is it a standard, available to purchase in small and sample quantities (even from private individuals), relatively low price and fast delivery? Is it still a scientific or engineering sample, or it is second and further generation device? Price and availability?
Performance questions	**Measurement range?** Will the sensor be able to accurately measure within the expected concentrations range in the intended environment? **Accuracy and stability?** Are the stated data quality sufficient for the purpose? How stable is the sensor performance under different conditions and over time? Drift? Missing data? **Expected life span** How long can the sensor be expected to operate, and what travel, physical effort and material price is required to maintain or exchange it?

Although a large number of relatively low-cost sensors (LCSs) are available on the market today, it can still be difficult to find suitable sensors for a specific purpose. Information regarding physical specifications such as size, weight, power consumption requirements, communication possibilities and weather resistance are generally provided by the manufacturer and it is relatively easy to make a first choice. Identifying a suitable sensor based on performance can be much more difficult. This is partly because the sensor's performance varies depending on a number of factors in their surroundings. The performance information provided by the manufacturer of commercial components is often based on controlled laboratory tests, which are not always fully disclosed for various reasons. And usually expecting full range of declared performance cannot be expected in field conditions – indoors or outdoors or combined for portable and mobile sensors. Furthermore, assessment of drift, stability and actual lifetime requires testing under a longer period and may vary from sensor to sensor. Detailed information on these factors may not be provided by the manufacturer or present a best-case scenario that may not apply to all units.

Including findings in scientifically published sensor tests in the selection, a specific sensor can also prove difficult. Due to the rapid technological development in combination with a relatively long publishing process, there was often a new version with promised improvement in performance of the sensor available on the market when the sensor test was published.

For the current setup in the LoV-IoT project, several evaluations were considered, most of which are mentioned in the above summary. Information found in the manufacturer application notes and scientific literature is still very useful to gain a good understanding of the general performance of a sensor type, the factors that affect the sensor performance (e.g. effect of meteorological conditions, cross-sensitivity, drift and lifespan etc.). It can also give a general idea of how large variance can be expected between different sensors. A good understanding of the weaknesses and strengths of a certain sensor type will likely facilitate the initial sensor selection and reduce the risk for selecting sensors that turn out to be unsuitable for the application in the end.

The LCSs selected in the LoV-IoT project were tested and evaluated to further assess their performance (Figure 9). An initial test was performed in a lab environment and then followed by a field test where the LCS were mounted on a reference station for evaluation of performance in field conditions. The LCSs were validated against a reference instrument to identify strengths and weaknesses. Our experiences generally agree with that of scientifically published sensor tests summarized in the previous sections. The number of LCSs tested of each specific type is too low to allow us to draw any scientific conclusions, and only general experiences will therefore be presented.

Most of the LCSs tested within the LoV-IoT project performed relatively well when tested in lab conditions. In outdoor conditions, performance was considerably reduced. We found a strong influence of, for example, meteorological conditions, indications of cross-sensitivity to other pollutants, a large variability in performance between LCS of the same type, and likely a shorter life time that stated by the manufacturer for some sensors. We also found a strong need for additional calibration and post-processing to ensure that data is reliable.

As many different sensors have been validated throughout the project, a sensor testbed was developed to standardize and make the validation procedure more efficient. This testbed will be further described together with the diagnostic tool developed for post-processing the data on the Internet of Things (IoT) platform in the following chapters.

Our conclusion is that, in the current stage, the LCSs should only be used as a complement to the reference measurement infrastructure and not as a stand-alone solution for measuring pollutant concentrations. They still have great potential for increasing spatial coverage in areas where this is needed, given that the reference measurements are available, and that proper post-processing is applied.

4.1 Identification and selection of possible sensors and sensor sets

In order to identify suitable sensors for the LoV-IoT air quality sensor platform, a market analysis on available sensors was made.

In order to identify and select suitable sensors and sensor sets for the LoV-IoT air quality sensor platform, a market review and analysis of available sensors was made. Different options explored will be described in the sections below, separate for each measured parameter.

There are some basic categories between all sensors, and it is important to define some basics:

Packaging

- Bare sensor die (silicon chip or setup only)
- Packaged sensor chip
- Functional OEM sensor module/finished instrument

Price (including maintenance, if needed)

- Low price – up to 30 USD
- Mid price – up to 150 USD
- High price – up to 300 USD or more

Signal processing

- Need custom electronics, board and software plus calibration
- Deliver calibrated values

Table 6: All currently used sensors in one air quality measurement sensor platform (all tested sensors in respective following sections)

Parameter Manufacturer, sensor name, separate amplifier-conditioner, power supply, interface	**Temp. deg C**	**Humidity, RH%**	**Gases NO2, ppb**	**Dust/ Particle PM2.5**	**Noise, dB**	**Other**	**Integration with processing/ comm. board**
Bosch BME280, No, 1.8-3.3V / I2C/SPI serial output 1.8-3.3V	x	x				x/atm. pressure	OEM + custom PCB board
Plantower PMS5003, No, 5V, I2C/UART serial output 3.3V				x		Ventilator, forced airflow	Connector/ cable connection
Alphasense NO2-B43F, Yes ISB, Vin 3.5-6.5V, analog output Vout 0 to Vin(-0.5V)			x			Each ISB is pre-calibrated for specific sensor	Connector/ cable connection
DFRobot SEN0232, No, Vin 3.3-5V, analog output Vout 0.6-2.6V					x		Connector / cable connection

4.1.1 Basic sensors – temperature/humidity

Variation in air temperature and humidity influences the signal from many different types of air quality sensors. Including information about these parameters is thus crucial to enable evaluation of the sensor's performance as well as correction of data. The evaluated sensors for air temperature and humidity are presented in Table 5.2, and some additional market data are given in Table 5.3, plus some pictures of sensors, sensor boards and devices.

Table 7: Identified and evaluated temperature/humidity sensors

Temperature and humidity sensor name	Evaluation test	Test place
Bosch BME280	Outdoor/next to reference	Sweden
Bosch BME680	From datasheets and external data	
Aosong DHT11	From datasheets and external data	
Aosong DHT22 / AM2302	From datasheets and external data	
Aosong AM2320 / AM2321	From datasheets and external data	Sweden
Honeywell Humidicon HIH5/6/7/8/9000 series	Outdoor/next to reference	Sweden/Chile
Sensirion SHT71	Indoor/environmental chamber	Sweden
Silicon Labs SI7021/ TEConnectivity HTU21	From datasheets and external data	
Texas Instruments HDC1080/2080	From datasheets and external data	
Aosong AHT10/AHT15/DHT12	From datasheets and external data	

Table 8: Identified and evaluated sensor, price and availability comparison

Manufacturers respectively	Price, USD, 1pc. (sensor only)	Availability 2020/08
Bosch BME280/680	6.6/13.40	Yes/Yes
AOSONG DHT11	5	Yes/Yes
AOSONG DHT22/AM23202	10	Yes/Yes
AOSONG AM2320/AM2321	4.00/?	Yes/?
HIH5000 (humidity only)	10	Yes
HIH6000	10 to 65	Yes
HIH7000	7 to 51	Yes
HIH8000	7.60 to 55	Yes
HIH9000	?	Obsolete
Sensirion SHT71	27.17	Yes
Silicon Labs SI7021/HTU21	3	Yes/Yes
TE Connectivity HTDU21D(F)	6	Yes
Texas Instruments HDC1080/2080	4.5/5	Yes/Yes

Table 9: Pros/Cons of identified and evaluated temperature/humidity sensors

Evaluated temperature/humidity sensors	Pros	Cons
Bosch BME280	Available, cheap, easy communication via I2C/SPI, many examples and external comparison. Available on board with voltage regulator and voltage translator on the interface side. No problem to just replace a sensor with a new one, no special measures needed. Also hasthe ability to measure atmospheric pressure– which is useful.	If the sensor reads too fast, that can cause overheating and steady offset in the values. Caution should be used when measuring in forced airflow and not.
Bosch BME680	Same as BME280, but in addition there is VOC (volatile organic compound) sensor on board.	Possible overheating again if the sensor is reading too fast, double the price.
Aosong AM2302 (DHT22)	Small size 15.1x25x7.7 milimeters, plastic package, assembled versions, 3–5V power and I/O, 2.5mA during conversion, good for 0–100 percent readings with 2–5 percent accuracy. Temperature accuracy is 0.5degC in interval of -40 to 80degC	Reports on frequently failed devices, not entirely clean datasheet.
Aosong DHT11, almost same as above DHT22	Even lower price	Slightly worse characteristics than DHT22. Not so good for measuring humidity up to 100 percent, nor negative temperatures.
Aosong AHT10/AHT15/DHT12 Honeywell HIH6/7/8/9	Available in many different packaging factors, with or without PTFE filter for 100 percent humidity measurement.	Can be expensive, depends of packaging and calibration.

4.1.2 Insplorion LUFT-NO2

Insplorion LUFT-NO2 sensor. Optical sensor based on precise measurement of the change in refractive index of a sensing material in the presence of a specific target gas. The Insplorion LUFT-NO2 sensor is not yet commercially available, but has been developed during the project by Insplorion AB. The sensor is based on a novel technology for gas sensing originally developed in collabora-tion with Chalmers University of Technology.

Throughout the project, a total of three embodiments of the Insplorion sensor have been tested. Based on the tests, improvements were made to reduce the impact of ambient conditions such as light pollution, temperature and humidity that could impact the optical response and adversely affect the concentration reading.

The Insplorion sensors where calibrated by exposure to controlled concentra-tions of NO2 (up to 100 ppb) and by comparison with readings from an EcoTech Serinus 40 reference NO2 measurement equipment. More information about the Insplorion LUFT-NO2 sensor is available on the Insplorion webpage: http://www.insplorion.com/en/air-quality-sensor/.

5 Case studies using SDS011/SDS019

In addition to the case studies using the LoV-IoT sensor platform, three case studies using the SDS011 and SDS019 sensors have been conducted. Firstly, a study in Santiago, Chile where SDS011 sensors measured in parallel with several reference stations. Secondly, a study in Gothenburg where the sensors measured at bus stations and on an electric bus. Finally, it was explored how and if the sensors can be used as a compliment for air quality monitoring around a construction site and for mobile measurements.

5.1 Field performance of a low-cost sensor in the monitoring of particulate matter in Santiago, Chile

The first part of the project, which was executed in 2018, refers to the bibliography, had as the main objective to measure and test the particle (PM) low-cost sensors behavior under local conditions in Chile, these conditions are mainly high levels of particulate matter and RH in winter.

To test the response and compare them with reference monitors, seven sensor units were tested for 8 days at an official monitoring station in Santiago. Sensor inter-comparison shows for PM_{10} an R^2 between 0.98 and 0.99, and $PM_{2.5}$ shows an R^2 between 0.99 and 1, so the $PM_{2.5}$ signal has a better intervariable. To quantify the reproducibility of the sensors, the nRMSE was calculated and the results show a better response for $PM_{2.5}$ (9–24 percent) than PM_{10} (10–37 percent). According to the correlation results, reproducibility analysis shows best result at $PM_{2.5}$ signal. In addition, the comparison between gravimetry method and the IoT sensors concentration (24 hours on average) shows an R^2 between 0.91 and 0.95 for $PM_{2.5}$, which indicates a good tendency for these two methods. HR > 95 percent values affect the results of the sensors.

All these analyses allow the use of low-cost sensors as an exploratory analysis, easy to implement and high temporal resolution but previous work needs to be done to ensure the quality of the data obtained from the sensors. As proof of this, a chemical characterization of the particulate material project was executed in Temuco City in 2019 with the support of the Environmental Ministry of Chile. The strategy used in the monitoring campaign is in line with the development of international network trends, using sensors as exploratory monitoring. The application of low-cost sensors as screening monitoring was successful, they did not present measurement problems despite being exposed to high levels of contamination, it was possible to determine concentration levels in 7 urban points without official monitoring stations, and it was also possible to identify the diurnal trends for each site.

5.2 Laboratory and field evaluation of low-cost SDS011 and SDS019 particulate matter sensors

In collaboration with partners in the Electricity project, Ericsson tested two low-cost sensors (SDS011 and SDS019), both in the laboratory and implemented in the field. In the field measurements, sensors were mounted at five bus stations and on public transport passing these stations.

In parallel with the ElectriCity installations, the performance of the SDS011 sensor was evaluated against the municipality's TEOM reference instrument at Femman air quality station. The sensor was installed for one month and as can be seen in Figure 20 SDS011 shows trends similar to TEOM with some offset on most occasions, but on some occasions, the sensor does not agree with the reference instrument. The figure shows that there is a relationship between humidity and deviation of these sensors from TEOM signal, but it does not explain how the relationship is due to the inconsistency in the relationship.

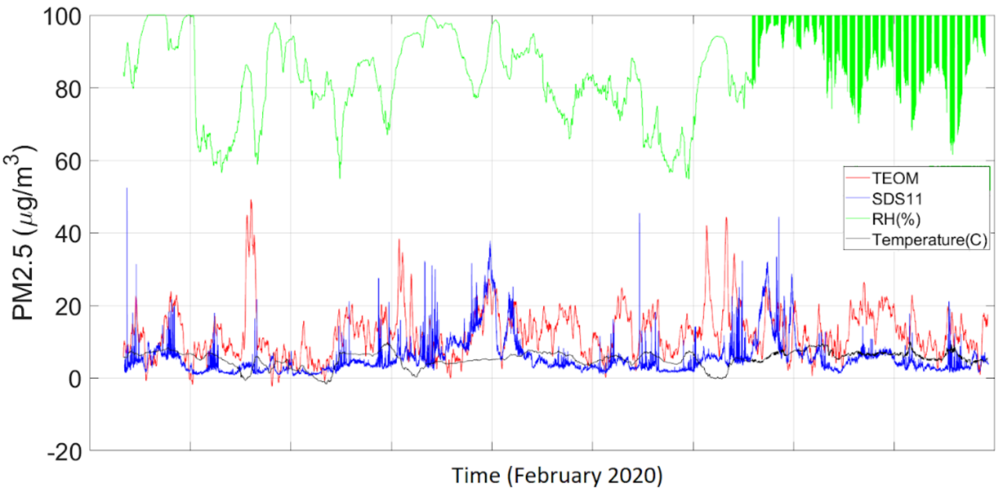


Figure 20. Field evolution of the SDS011 sensor compared to the TEOM at Femman air quality station.

In laboratory tests at Chalmers, the performance of the SDS011 and SDS019 sensors was compared to TSI-OPS-3330, which is another optical particle sensor. Figure 21 shows two data sets from the laboratory experiments in two different concentration ranges of ammonium sulfate particles generated in the laboratory. Both sensors show similar trends to the reference instrument with some offset. SDS011 and SDS019 signals are very close to each other. SDS019 consists of 4 SDS011 sensors and a pump to adjust the air flow to the inlet to the 4 sensors and the built-in sensor for temperature and humidity. The performance of SDS019 was slightly better than SDS011 for three main reasons:

1. Air flow adjustment
2. Redundancy of sensors
3. Possible corrections for errors associated with temperature and humidity.

However, these sensors are optical and they work on a different physical principle compared to TEOM. Therefore, they have fundamental differences. They show similar trends in the concentration over time, but their absolute values differ from the reference instruments. On the other hand, their advantage compared to the reference instruments is their small size and low weight and their cheap price which enables many applications for them in mobile and stationary units.

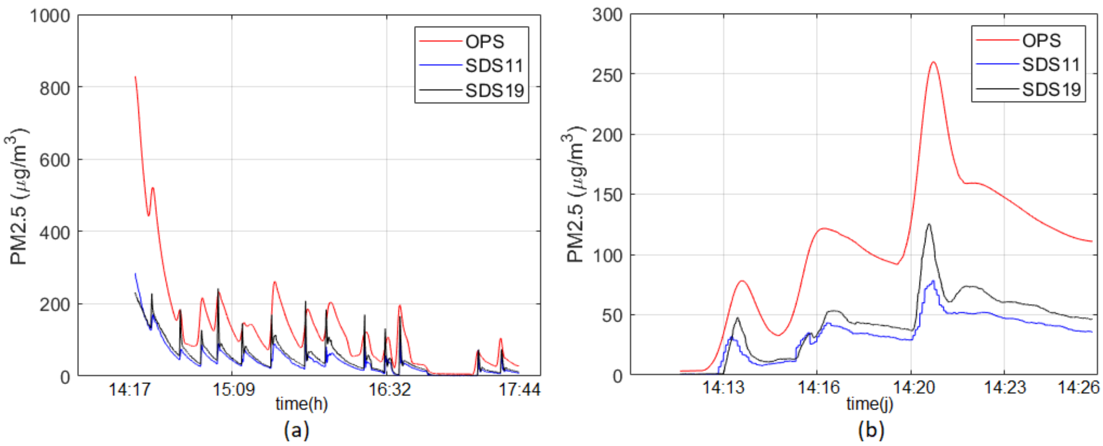


Figure 21. Laboratory experiments on SDS011 and SDS019 compared to TSI-OPS-330 as a reference in two different concentration ranges.

In the field implementations, there were not a reference sensor other than the tested sensor and most focus was on the solutions for IoT and mobile application of these low-cost sensors. Two types of networks were tested, and the performance of the solutions were evaluated. Stationary units of SDS011 were installed at bus stations in Gothenburg. Since Wi-Fi was provided at the stations, Raspberry pis were used as computers to transfer the MQTT message to the IoT brokers of Ericsson servers. The Raspberry pis showed some issues with the Wi-Fi and network stability; however, the problem was resolved after some iterative corrections in the scripts. Mobile units with PyCom and mobile network (requires a 4G/5G sim card instead of Wi-Fi) were tested and the data transfer was successful and stable. The PyCom devices are most useful when used in a mobile unit on a bus or a drone, etc. or when Wi-Fi is not available in a stationary application. Both PyCom and Raspberry pi were also tested for the mobile units on the bus and both showed reliable stability. The bus unit with raspberry pi is still installed and runs and displays real-time data from SDS019 and SDS011 while storing the historical data to feed a long-term database. The SDS019 and SDS011 can measure with a time resolution of one second but since they have a limited lifetime and it is not necessary to have new data every second, they were programmed to measure every five minutes and then sleep. This method is also better for the database and is recommended. In addition, it is more sustainable since the sensors last longer and they should be replaced with new units less frequently. However, it can be easily updated and adjusted in the code configurations. It is also recommended to have an option of remote access to code configurations for the setups. This is not implemented but recommended for the future attempts. An example of this IoT application is shown in Figure 22.

Figure 22. Implementation of low-cost particulate matter sensors as mobile and stationary units in the City of Gothenburg.

5.3 A study of the Haga construction site and the use of low-cost sensors

In this study a network of low-cost particle sensors (SDS011) was installed around a major infrastructure construction in central Gothenburg, Sweden. Urban air quality is a key health factor for city residents and newly developed small and inexpensive sensors have been promoted as means to assess and track air quality hotspots and point sources. In this case, the construction site was chosen as a potential particulate matter hotspot, and a network of eight sensors was placed around its perimeter for a two-month period at the end of 2019. In addition to the sensors, an air quality monitoring station belonging to the City of Gothenburg in close proximity was used for reference measurements and comparisons with historical trends.

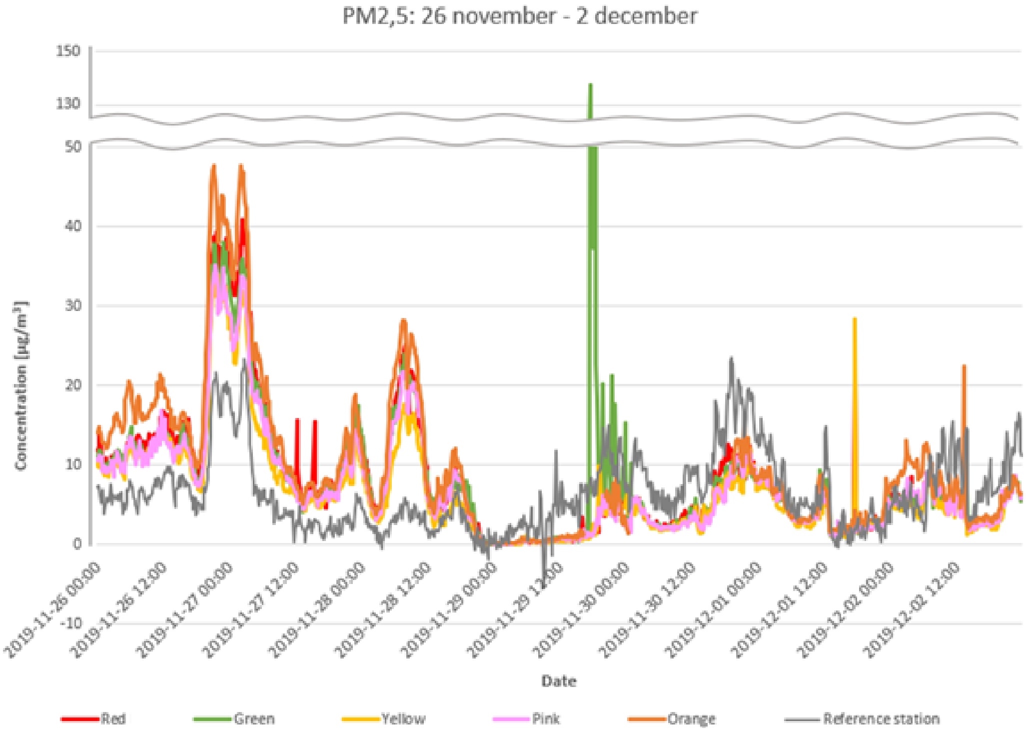


Figure 23. PM2.5 data from five SDS011 placed at different locations and at one reference station placed in Haga.

The results showed the importance of the weather for the performance of the particle measurements. The dominant wind direction leads to that seven out of eight sensors did not measure direct emissions from the construction site for most of the time, which means that it is more likely that sensors captured resuspended particles from the surrounding roads. If the sensors had been placed around the edges of the construction site, in all wind directions, they could have measured the direct emissions from the site. In addition, the relative humidity was high during both analysed months, which caused problems because SDS011 according to the manufacturer only work properly when the RH does not exceed 70 percent. To determine if SDS011 can work as a complement for air quality control around construction sites, additional tests would have to be performed.

6 Experiences and recommendations

The main lessons learned from working with LCSs are to:

1. ensure sufficient data quality through validation and post-processing
2. limit the use of this type of sensors to appropriate situations
3. to maximize the flexibility and openness of the sensor platform components.

When using LCS technology, it is important to validate the sensor’s performance by comparative measurements with reference instrumentation during representative ambient conditions. Commonly found biases in the currently available LCSs include systematic offset, influence by meteorological parameters, cross sensitivity to other pollutants and drift. To obtain reliable data, it is necessary to post-process the sensor data using algorithms developed from comparative measurements with reference instrumentation in representative ambient conditions. We found postprocessing algorithms developed for each individual sensor using machine learning techniques were required to optimize the data quality.

The following appropriate applications for LCS technology were identified in the LoV-IoT project: in citizen science and for communication purposes, to complement and extend reference measurements, in studies with limited spatial and temporal extent, for identification of patterns rather than absolute concentrations, and for an initial rough measurement and indication, for example in an early warning system in situations when rapidly changing pollutant concentrations may occur.

With the rapid development of both LCS and communication technology, any sensor platform. will rapidly be outdated, unless it is possible to replace parts as new and improved options are available. As LCS-performance is still problematic, allowing exchange of LCS and communication technology will ensure that the data quality can be improved as new solutions are available. The same applies to data communication control cards where new possibilities arise continually. It can therefore be useful to plan for flexibility to allow transfer of the work to a better product if one arrives. To enable this, the communication program can be divided into modules and layers. This will facilitate transfer of the program to another control card if needed.

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Appendix A: Example of sensor data in JSON format


```
{
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  "devicetype":"UBLOX_C030_U201",
  "location":{
    "latitude":"-32.74855",
    "longitude":"-71.47478",
    "altitude":"-0.5"
  },
  "sensorreadings":[
    {
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        "sensorid":"8388e9c2-e391-4100-bf3f-9cdf7232f29d-04",
        "sensortype":{
          "id":"04",
          "name":"BME280"
        }
      },
      "timestamp":"2020-06-01T06:59:12Z",
      "sensordatavalues":[
        {
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          "value":7.97,
          "stddev":0.01,
          "valuetype":"temperature",
          "unit":"degC"
        },
        {
          "id":"val-2",
          "value":1022.49,
          "stddev":0.04,
          "valuetype":"pressure",
          "unit":"hPa"
        },
        {
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          "stddev":0.01,
          "valuetype":"humidity",
          "unit":"%"
        }
      ]
    },
```

```
{
  "sensor":{
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    "sensortype":{
      "id":"03",
      "name":"PMS5003"
    }
  },
  "timestamp":"2020-06-01T06:59:12Z",
  "sensordatavalues":[
    {
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      "value":54,
      "stddev":0.99,
      "valuetype":"PM2.5",
      "unit":"µ g/m3"
    },
    {
      "id":"val-2",
      "value":43,
      "stddev":0.58,
      "valuetype":"PM2.5 atm",
      "unit":"µ g/m3"
    },
    {
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      "value":27,
      "stddev":5.99,
      "valuetype":"DB2.5",
      "unit":"pcs"
    },
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      "unit":"µ g/m3"
    },
    {
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      "unit":"µ g/m3"
    },
    {
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      "value":2,
```

"stddev":1.66,
"valuetype":"DB10",
"unit":"pcs"
}
]
},
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"value":0.0745,
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}
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Environment Administration, City of Gothenburg
Box 7012, SE-402 31 Gothenburg
Telephone: + 46 (0)31 365 00 00
E-mail: miljoforvaltningen@miljo.goteborg.se