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A User-Based Look at Visualization Tools for Air Quality Data harvested by micro-sensor units

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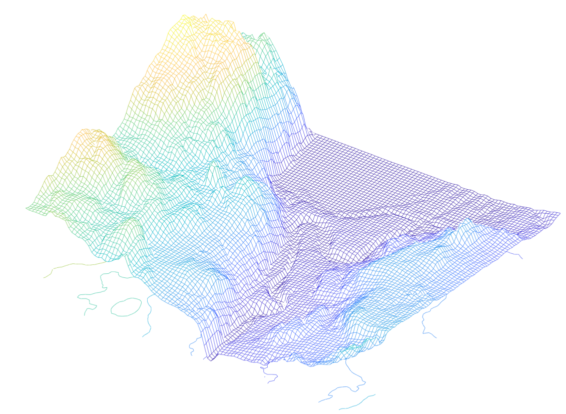

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A User-Based Look at Visualization Tools for Air Quality Data harvested by micro-sensor units

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Cybernetics and Robotics
Submission date: July 2020
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Abstract

The aim with this thesis is to perform a user-based look at visualization tools for air quality data harvested by IoT units in Trondheim. Several visualisations, including time-series graphs, a 2D heat-map and a noble 3D simulated environment have been developed and tested on 9 selected users. The scope of this project have been users in the three categories: citizens, researchers and policy makers.

In addition three low-cost micro sensors, developed by Exploratory Engineering, was used to gather air quality data over a period of two months. Two of the sensors where mounted on stationary locations, at Lerkendal and Voll, and the third was placed on top of a moving bus. All of the sensors was monitoring in real-time and automatically transmitting the results to cloud server via Narrow Band IoT.

In Norway, particulate matter ($PM_{2.5}$ and PM_{10}) and nitrogen dioxide (NO_2) are the most important components of local air pollution [1]. Other pollutants such as carbon monoxide (CO), sulphur dioxide (SO_2) and ground level ozone (O_3) can also contribute to poor air quality, and can cause serious health problems for humans, animals and vegetation.

Our aim is to visualise the complex "invisible" air pollution data, such that citizens, researches and policy makers can take a decision, to improve a routine or to change a method towards reducing the emissions of harmful gases and particles.

We have reviewed related work of air quality visualisation, and projects that include low-cost air quality sensors. Further we developed three types of visualisation platforms, including a line-graph dashboard, a 2D heat-map and a 3D heat-map. Finally our visualisations was validated by a group of users through multiple video interviews.

Our findings from the experiment performed shows that mobile air quality sensors are prone to power and connectivity failure. We also discovered that a 2D heat-map visualisation is the preferred way to present the data among all three user groups in a decision making context.

All code developed for our visualisations is published online on GitHub: `https://github.com/danieasv/TTK4900-master_thesis/`

Sammendrag

(Norwegian translation of the summary)

Målet med masteroppgaven som har tittel ”User-based look at Visualization tools for Air Quality Data harvested by IoT units” er å utvikle og brukerteste forskjellige visualiseringsverktøy rettet mot luftforurensning i Trondheim. Tre ulike platformer har blitt utviklet, deriblant et verktøy for analyse av historiske data, et 2D-varmekart og et 3D simulator fra Trondheim. De ulike platformene har blitt brukertestet på utvalgte personer fra gruppen **innbyggere**, **forskere** og **beslutningstakere**.

I tillegg til data fra offesielle målestasjoner ble data fra tre mikro-sensorer utviklet av Exploratory Engineering benyttet for å samle inn luftkvalitetsdata over en periode på to måneder. To av sensorene ble fastmontert ved Voll og Lerkenal, og den tredje på taket av en buss i rutetrafikk. Alle sensorene registrerte data i sanntid og lastet opp resultatene direkte til en server via Narrow Nand IoT.

I Norge er svevestøv ($PM_{2.5}$ and PM_{10}) og nitrogrendioksid (NO_2) de to viktigste komponenetene i lokal luftforurensning[1]. Andre miljøgifter som karbonmonoksid (CO), sulfurdioksid (SO_2) og bakkenær ozon (O_3) bidrar også til dårlig luftkvalitet, og kan gi alvorlige helseskader for mennesker, dyr og vegetasjon.

Vårt mål er å visualisere luftforurensning slik at innbyggere, forskere og beslutningstakere kan forbedre rutiner og/eller endre metoder, slik at utslippene av skadelige gasser og partikler kan reduseres. Vi har undersøkt tidligere prosjekter innen visualisering av luftforurensning, samt prosjekter med bruk av lav-pris luftkvalitetssensorer. Vi utviket tre forskjellige typer visualiseringsplattformer, deriblant linjegraf, 2D varmekart og 3D varmekart. I slutten av prosjektet ble visualiseringene evaluert av en rekke brukere gjennom videointervjuver.

Våre resultater viser at mobile luftkvalitetssensorer er utsatt for tap av batteri og nettverksforbindelse. Vi oppdaget ogsså at 2D varmekart er foretrukket metode blant alle de tre brukergruppene for å visualisere data når en beslutning skal settes.

Kodemateriale for de ulike visualiseringene er tilgjengelig på GitHub: `https://github.com/danieasv/TTK4900-master_thesis/`

Preface

This thesis presents experiments conducted during the spring semester of the final year of the five-year Master´s Degree Program in Cybernetics and Robotics at the Norwegian University of Science and Technology (NTNU). I would like to warmly thank my supervisors Prof. Kerstin Bach and Tiago Veiga at the Department of Computer Science (IDI), and my external supervisor Sigmund Akselsen from Telenor for excellent guidance and rewarding discussions. I would also like to thank Trondheim Municipality for providing the wood burner data set and Exploratory Engineering for letting me use their micro air quality sensors. Lastly I would like to thank my girlfriend and family for invaluable support and motivation throughout the semester.

Daniel Svendsen
Trondheim, Norway
July 2020

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Chapter 1

Introduction

1.1 Motivation

Air pollution is considered to be the world's largest health threat. Data from the World Health Organization (WHO) estimates that air pollution kills more than seven million people worldwide every year. Air pollution has both acute and chronic effects on human health, ranging from respiratory irritation with asthma to cancer and heart problems [36]. About 8 out of 10 people living in urban areas are exposed to air quality that exceeds WHO guideline limits.

Air pollution is also seen as a growing challenge for municipalities in Norway, especially in the biggest cities such as Oslo, Bergen and Trondheim, where higher population densities and high air pollution coincide. The European Environment Agency (EEA) publishes yearly a report of the air quality in Europe. They estimated about 1500 premature deaths in Norway in 2016 due to exposure to high air pollution levels ($PM_{2.5}$, NO_2 and O_3). The smallest impacts are found in the Nordic countries, while the largest health impacts are observed in countries with the largest populations, namely Germany, Italy, Poland, France and UK [30].

According to Regulations Relating to Pollution Control Act (*forurensningsforskriften*) in Norway, municipalities are responsible for keeping the air quality within given guideline limits. In order to keep this obligation, protect the outdoor environment against pollution and reduce existing pollution, data are collected and models are developed to plan and coordinate activities to limit pollution problems, since the probability to chronic illness rises with the amount and exposure to high levels of air pollution. In order to keep the levels low and prevent multiple coherent days with bad air quality, street cleaning combined with a liquid containing magnesium chloride ($MgCl_2$) is an effective activity to reduce dust particles on the roads.

The science of air quality is complex, and many aspects of the problem are not fully comprehensible. However, it can be seen that the effects of air pollution on health depend not only on exposure but also on the vulnerability of people. Age, pre-existing health conditions or specific sensitivity are factors that can affect the impacts of air pollution. Air pollution also has significant economic impacts, with increasing medical costs and reduced productivity across the economy through lost working days.

When we look at the specific elements affecting the health, we often find the four main substances: nitrogen oxides (NOx), sulphur oxides (SOx), ground-level ozone (O_3) and particulate matter (PM) distinct. The term particulate matter, also known as particle pollution or particulates stands for a mixture of solid particles and liquid droplets found in the earth's atmosphere. Some particles such as dust or smoke can be seen with the naked eye, while others are too small that an electron microscope is required to be able to detect it.

There is a rising demand for data availability and knowledge sharing. The Norwegian Road Authority, the Norwegian Environment Agency and the Norwegian Meteorological Institute are all collaborating to this transition and provide scientific reports, data exchange and models to support the work to reduce air pollution.

1.2 Problem

The European Commission Directive 2008/50/EC require EU member states to monitor air quality for 13 key pollutants in cities with a population larger than 250 000 people, and includes O_3, NO_2, SO_2, and particulate matter (PM). In addition, the directive indicates that modelling should be applied to give a broader spatial explanation of the measurement data. Norway, as a European Economic Area (EEA) member, adopted these regulations in 2008. These legal requirements gives a need to create accurate urban air quality models.

Air quality models are used to calculate the emission concentrations of pollutants, based on environmental input such as weather data, and data from official air quality reference stations. By using mathematical equations, which represent the physical and chemical processes in the atmosphere, models can be solved numerically on computers and forecast the air quality at a high spatial resolution.

A large number of epidemiological studies have shown that short term exposure to particulate matter in outdoor air is correlated with total mortality [35]. [35] This eventually led to the outdoor air pollution standards for PM_{10} and $PM_{2.5}$ in the European Union. Particles are normally classified according to their size, as either coarse or fine grade. Fine particles have a diameter of 2.5 μm or less ($PM_{2.5}$), and coarse particles are 10 μm or less (PM_{10}). Particles larger than 100 μm in diameter is likely not to stay airborne long enough to be measured. To put this in context, a human hair is about 70 micrometres in diameter.

$PM_{2.5}$ illustrated in red in Figure 1.1 is especially of great concern, since these tiny particles are able to penetrate deep into human lungs [55]. Among environmental effects are poor visibility (smog) to more serious outcomes such as acid rain, which pollutes soil and drinking water.

Recently scientists discovered that the SARS-CoV-2 virus was present on the particulate matter during the spreading of the infection [58]. Another event that illustrates the effect

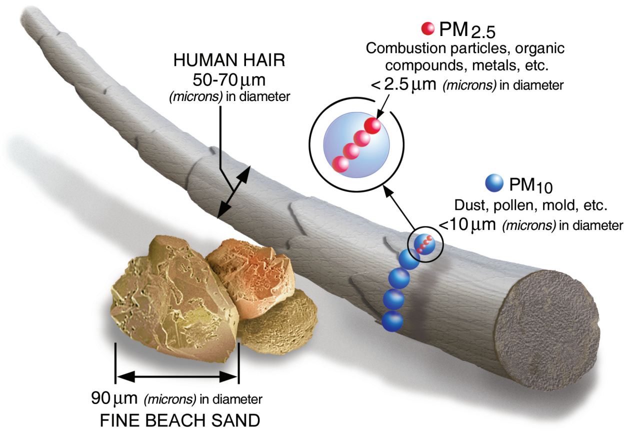


Figure 1.1: The illustration show the size and scale between human hair and particulate matter. Image courtesy: [5].

of particulate matter on human health is the Great Smog in London in 1952, caused by coal burning and thermal inversion, that trapped the pollutants at ground level. More than 4000 deaths were linked to this event, causing the establishment of the Clean Air Act. Many countries are now committed to national and international clean air legislation and air quality standards [56]. These agreements require regular reporting of air quality, including PM_{10} and $\mathrm{PM}_{2.5}$ concentrations.

Pollutants such as particulate matter and ozone are not necessarily produced from local sources, but rather transported by the wind over long distances. The Nansen Environmental and Remote Sensing Center conducted a research on the spread of particulate matter from a residential wood burner in Bergen and found a strong correlation between the distribution of wood burners and the ground-near concentration of PM2.5 [65]. Results from emission and dispersion modelling made by the Norwegian Institute for Air Research (NILU) show that replacement of old wood stoves for new ones could have up to 46 % reduction of emissions and up to 21 % of $\mathrm{PM}_{2.5}$ levels [44].

Gases like Carbon oxide(COx) and Nitrogen oxide(NOx) are produced by high-temperature combustion processes, with industry and traffic being the most prominent sources. Other important sources of pollution in Norway are residential wood burning and ship traffic.

1.3 Goals and research questions

The research goals with the following questions defined below point out the purpose of this thesis, and will be further evaluated in the Discussion chapter.

Research goal 1: Definition of situations and stakeholders that need information about air quality

- **RQ1:** Which stakeholders need the information about air quality?
- **RQ2:** What are the decisions for stakeholders to be made?

Research goal 2: Provision of data

- **RQ3:** What information do stakeholders need in order to make a decisions?
- **RQ4:** What are the benefits and challenges of using micro-sensors for air quality monitoring?

Research goal 3: Visualisation

- **RQ5:** What are the possibilities of air quality visualisation?
- **RQ6:** Which visualisation do the stakeholders find useful?

1.4 Thesis structure

The thesis is divided into eight chapters. Chapter 2 describe related work and previous projects for air quality monitoring. Chapter 3 describe the background for the project, introduce visualisation methods and Internet of Things. Further, Chapter 4 describe the implementation and architecture of the sensors we are using. In Chapter 5, the three visualisations developed and the bus experiment are described. Chapter 6 express the results and feedback from the experiment. Chapter 7 follow up with a discussion on the evaluation and results. Lastly, Chapter 8 contain a summary and conclusion of the work presented, and round off with a section with future improvements and ideas.

Chapter 2

Related work

The goal of this chapter is to provide an overview of state-of-the-art research within the field of air pollution visualisation, and previous work related to air pollution from NTNU.

2.1 Drive-by sensing

The idea of using air quality sensors on moving road vehicles, like buses or garbage trucks to facilitate the collection of dense spatio-temporal data sets in urban areas is not new. A project called City Scanner [10] at MIT used the term *Drive-by sensing* for this solution. In addition to utilizing a network of moving vehicles, drive-by sensing offers a number of advantages over more traditional approaches, like remote and stationary sensing. In many environmental use cases, the data collection have been constrained in a spatial or temporal dimension, which often limits the information to be extracted. For example, a stationary air quality sensor may collect precise airborne pollutants in one location, but miss the local differences in the nearby streets or neighbourhoods due to their sparse distribution [62]. On the other hand, remote sensing with satellite-based measurements can be used to cover air pollution concentrations over large land areas in one snapshot but constrained down to a temporal resolution. Such a method also requires a robust mathematical model to predict the changes in detail, since the atmosphere affects the satellite images of the Earth's surface. A lack of detailed knowledge of the optical properties of aerosols has also been challenging in this method [43], although the method has been accurate in certain applications such as water quality studies, where high temporal resolution is not required does not require a high temporal resolution [32].

The Norwegian Institute for Air Research (NILU) has done extensive research on how we can use low-cost sensors and systems for air quality monitoring. One example is the EU project City Sense[24] coordinated by NILU, which was the largest network of low-cost sensors in the world at that time. In 2015-2016, more than 330 low-cost sensors were measuring the air quality simultaneously across nine cities in Europe[1].

Figure 2.1: Screenshot of the CityScanner application from MIT [10]. Users can explore harvested data over space and time.

2.2 Clean A/R

Since pollution particles are subtle and difficult to spot with the bare eye, visualising the particles in a digital twin, could help in raising the awareness of the air pollution we are surrounded by. A user study done by Surround Vision[2] - A VR/AR production studio, shows that Virtual Reality focused games can help to engage people on a deeper level, with a positive result in education, influence and behaviour change. They created an application called **Clean A/R**, that used modelled air quality data from Kings College London to help visualise the pollution in cities of Great Britain using augmented smog effect [50]. Figure 2.2 illustrates smog in Augmented Reality (AR) from a street in London by using the application.

2.3 NTNU and Air Pollution

Previous master thesis from Ole B. Andreassen and Andreas J. Lepperød [9, 40] focused on how to develop accurate prediction models for outdoor air quality, based on historical data of weather conditions and air pollution levels from public reference stations. The data-driven prediction model from Lepperød was superior in 24-hour forecast compared to the traditional knowledge-driven forecast model from NILU. With machine learning, he was able to predict the general pattern of air pollutants, and foresee sudden spikes of high levels.

[1] https://www.nilu.com/research/urban-air-quality/low-cost-sensors-for-monitoring-air-quality/ (site loaded: 20.06.2020)

[2] https://surroundvision.co.uk/unity-for-humanity/ (site loaded: 13.6.2020)

Figure 2.2: Clean A/R is a tool that informs users about their ”invisible” surrounding air quality. Image courtesy: Surround Vision [50]

Another interesting project to mention is the Lufta application. Lufta is a monitoring app developed by bachelor students at NTNU [57]. The mobile application was designed in cooperation with Telenor, to fetch data from official reference stations, and visualise the levels with colour markers on a map. With the app, the user could check historical air pollution data from the nearest reference station, together with a description of the health risk with a corresponding color and smiley icon. Screenshots of the applications are presented in Figure 2.3.

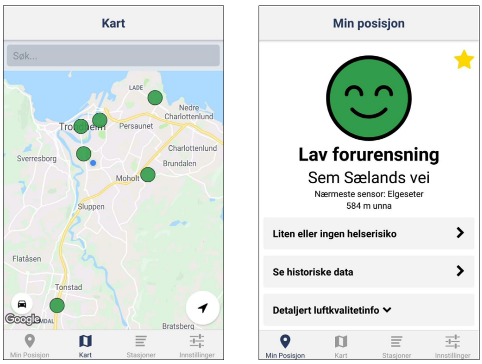


Figure 2.3: Screenshots of the Lufta application [57], with a map view of the reference station locations and a view with detailed information.

Chapter 3

Background

In this chapter, a framework for the theoretical background will be presented with theories of urban air quality and visualisations. Lastly give an introduction to Internet of Things (IoT) and low-cost sensors for air quality assessment are given.

3.1 Urbanisation

More than half of the global population live in cities, and the UN-Habitat researchers have estimated that this number will increase to two-third by 2050 [33]. This rapid growth of humanity represent new challenges for city planners and has put considerable pressure on available space and resources. Most of this population growth is expected to be in cities of developing countries, which are anticipated to grow by additional 1.3 billion people by 2040, compared to 100 million in cities of the developed world by the same period [6]. An estimated growth from the UN World Urbanization Prospect is illustrated in Figure 3.1. The rural population of the world has grown slowly since 1950 and is expected to reach its peak in a few years. Africa and Asia are home to nearly 90% of the world's rural population, with India and China having the largest rural population.

3.2 Digital Twins

We live in a digital revolution, where sensors and digital infrastructure becomes even more embedded in our industries, cities and daily lives. The term *digital twin* is used on a copy of a physical process, that usually matches the process in real time. In comparison is a model defined as a system that mirrors the operation of another, different system. Since models are simplifications of the reality, they do not aim to replicate the original system in the same detail; hence such abstraction differs from a digital twin. However, there is presumably some models that are closer to the real object than others [14]. To facilitate

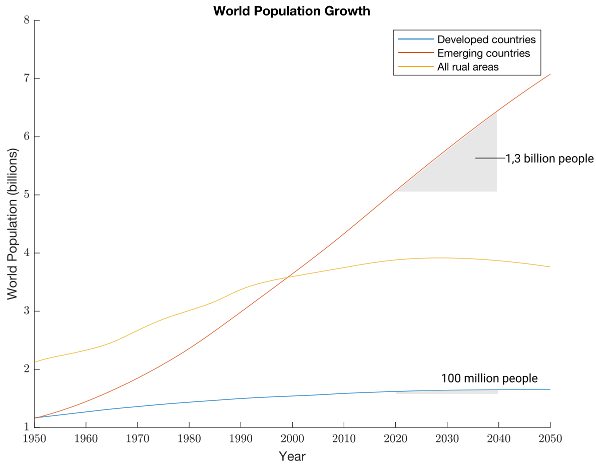


Figure 3.1: The illustration shows how the world population evolves from 1950 to 2050 in developed, developing and rural cities. Data is taken from UN World Urbanization Prospects (2018).

real-life perception, digital twins can be implemented in virtual reality (VR). During the work with this thesis, we developed a prototype for an urban digital twin to visualise air quality of the city of Trondheim in Norway. An accurate 3D model of the city for the game platform Unity was provided by Rambøll AS - a leading engineering, architecture and consultant company. Layers such as water and clouds and lightning were added separately, to give an authentic look. Data of the road network was downloaded from Open Street Map and edited in Blender to add a possibility to simulate driving traffic in the urban city model. The combined system can be applied and visualised on multiple layers and in different categories of information in virtual reality (VR) to focus the awareness of urban air pollution and help decision support.

The advantage of using a VR environment is that different participants from professional backgrounds can be informed simultaneously. A recent case study of a digital twin for smart cities was done with great success in Herrenberg in Germany [21]. With an urban mobility simulation, wind flow information and data from volunteered geographic information (VGI) in a 3D model environment, they presented a platform that could significantly aid teamworks and collaborative processes.

3.3 Smarter cities

Cities are complex systems connected with economic, ecological and demographic dynamics [21]. Gershenson (2008) [26] defined in his preface:

> A complex system is one in which elements interact and affect each other so that it is difficult to separate the behaviour of individual elements. Examples are an ant colony, the Internet, a city and an ecosystem.

One of the main features - and challenges with complexity is that it can be found almost everywhere; hence this makes it difficult to define. Within these complex systems, problems are addressed and overcome by allying innovative and technological ideas, such as traffic routing, car-sharing, smart energy grids, smart housing and more.

3.4 Internet of Things

The term *Internet of Things* was first used in the early 1990s with the outbreak of the internet, for the concept to control electronic equipment's ("Things") remotely [7]. Since then, the concept has evolved, and we often use the definition for devices around us connected to the internet. The device can use sensors, actuators or a combination of both, with an internet connection to control and sense the environment. For example, a temperature sensor near the road could report the temperature and notify the driver when the road is icy. By visualising the data from the temperature sensor, a maintenance team could then decide when to take action and de-ice the road, and keep it proper to use. The Internet of Things Global Standards Initiative (IoT-GSI) defined the concept as "a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies." [27]

IoT technology can simply be explained as the bridge between humans, computers and things. According to Siemens research, near 26 billion devices will be connected to the internet by 2020, and in 2025 the total number of connected devices in the world will be approximately 74 billion.

The applications for IoT can be divided into several categories. Gubbi et al. use the four categories: Personal & Home, Enterprise, Utilities and Mobile [28]. Personal and Home is the consumer category with smart wearable and smart homes. Enterprise refers to applications in work or industrial setting. This could be smart lighting or ventilation. The Utilities domain is usually for service optimisation rather than consumer consumption. An example could be smart water monitoring or electricity meter for municipalities. The last category, Mobile, is used for IoT in the transportation sector. One example here could be vehicle routing and fleet management of autonomous cars. This thesis will cover the Utilities sector, that belongs to the category of smart environment and air quality applications.

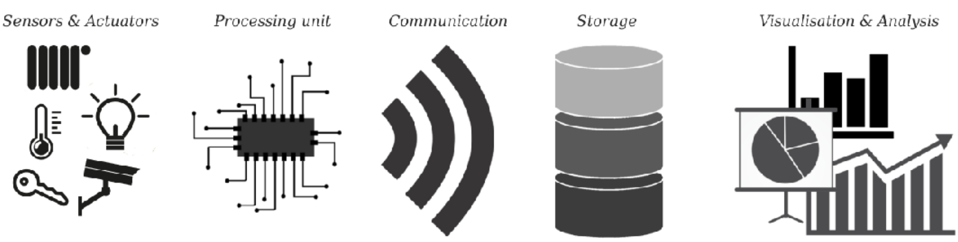


Figure 3.2: Main building blocs of an IoT System. Illustration adopted from [8].

The main building blocks of an IoT system can be seen in Figure 3.2. The first block is sensors that sense the environment or actuators that affect the surroundings. The sensor or actuator is then connected to a processing unit that converts the analogue signal into a digital signal value. The processing device is then connected with a trans-receiver to communicate the data to a server or endpoint device for storage. Lastly, a suitable visualisation layer is added to present and analyse the data for the user.

In general, the common core components of a low-cost sensor system may include [41]:

- A sensing element or detector
- Sampling capability, e.g. pump or passive inlet
- Power systems, including batteries and voltage regulator
- Signal processing unit
- Local data storage, e.g. flash memory
- Data transmission functionality (WiFi, 3G/4G, NB-IoT)
- Software for data treatment on server
- Housing and weatherproofing

3.4.1 Sensor & Actuators

A sensor is a device which detects or measures a physical property. This could be a thermistor, accelerometer, camera or GPS. In comparison to a sensor that measures data and sends it further, an actuator is a device that receives data, and then affect the surroundings according to the data. A few examples of an actuator are electrical motors, potentiometers and hydraulic cylinders.

Particulate matter can be measured using an optical particle counter (OPC), a low-cost air quality monitor. The sensor counts particles in different diameter size bins using a small laser; then an algorithm is used to convert these counts into mass estimations. While measurement errors are inevitable, such a monitor is much cheaper than other systems and gives a general understanding of polluting hotspots.

3.4.2 Processing unit

The processing unit is the brain of the IoT system and is often made up by a microcontroller - a so-called system on chip (SoC) containing I/O-peripherals, timers and flash storage. It is common to use a ready-made platform rather than designing a custom solution. Two popular platforms are Arduino and Raspberry Pi. These platforms have large communities that develop and maintain software libraries and comes with well-documented guides to use them. The benefit of using such platforms is that the developer does not need to have knowledge about the underlying hardware, and hence lower the threshold to get started with IoT-applications [19].

3.4.3 Communication

One of the first ”Things” defined as an IoT device were Radio-Frequency Identification (RFID) tags [11]. This tags can be used to monitor objects in real-time in a near-field communication range. They can either be passive or active. Passive tags harvest the energy required from the signal transmitted by the RFID-reader, while active tags need a power supply from batteries, with a longer communication range. The IEEE 802.15.4 standard is used by many commercial network solutions, for example in WiFi, Narrow-Band IoT, Zigbee and LoraWAN. Another typical communication protocol among wearable products and low power devices are Bluetooth Low Energy (BLE), as well as cellular GSM/4G/5G communication when long distances are needed.

3.4.4 Storage

Now that the processed data is available, it should be stored in a flexible and structured way to be usable. There are mainly three forms of IoT data storage [42]:

- *local:* Data sampled by the sensor is stored in the local storage unit (flash memory) of the device.
- *distributed:* Data is stored in some nodes in a network through distributed technologies.
- *centralized*: Data collected by the node is stored in a common data centre.

The centralized method is the preferred way of storing data. Because of limited storage capacity and battery power, local and distributed forms are not suitable for a large network of IoT nodes, or when data is shared across different applications [63]. Not Only SQL (NoSQL) is a typical way of storing and managing unstructured data in IoT applications. In comparison to Structured Query Language (SQL) - a relational database, NoSQL systems separate data storage and data management, hence they are schema-free. This means that the data stored in a NoSQL system does not need to fit well into relational tables or have a pre-defined data model. MongoDB is a popular open-source NoSQL system, and SQLite and PostgreSQL are two popular, open-source SQL system. The main benefits of storing the data in a centralized cloud system are accessibility and scalability, which are also two important factors when working with IoT systems.

3.4.5 Visualisation & analysis

Visualisation of data is critical for IoT applications, as defined by Gubbi et al. [29] It is about ”extracting meaningful information from raw data”. The process is non-trivial and requires a combination of event detection and visualisation of the raw data with information represented according to the requirements of the end-user. Marjani et al. [48] stress how difficult visualisation of big data can be because of the large size and dimensionality, or if the data are unstructured.

When a large amount of data from IoT systems are collected, it would be meaningless to analyse it one by one. Instead, it is common to highlight important trends and characteristics in the data using visualisation techniques, such that the user can interpret the information in a meaningful way. There are five main visualisation techniques to consider, including Geometric projection, Pixel-oriented, Icon-based, Hierarchical and Graph-based. We will describe each of them one by one in the section below with some relevant examples.

Data from IoT systems is rarely represented as only one single value. Instead, it is often recorded with multiple attributes, e.g. time, temperature, location combined. Each attribute stored corresponds to a dimension. It is, therefore, common to consider multidimensional visualisation when working with IoT data.

3.5 Mapping and Visualisation Methods

Visualisation of data is a process which aims to communicate data clearly to the user through graphical representation. As described in the previous section we have five main visualisation methods to consider [59]:

3.5.1 Pixel-oriented Projection

With pixel-oriented visualisation we aim to map each data value to a colored pixel. Since this allow only one pixel per data value, we can only visualise data in one dimension. If we want to visualise multidimensional data, subviews can be used and placed side by side, such that the relative data points are placed in the same location. In that way correlation and dependencies could be more easy detected across the dimensions [39]. An example of a pixel-oriented visualisation is displayed in Figure 3.3, where the age of a population is represented with a shade of grey.

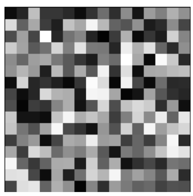


Figure 3.3: Example of a pixel-oriented visualisation. Image courtesy: [8]

3.5.2 Geometric Projection

A geometric projection visualisation is used when we want to visualise more than one dimension in the same plot [39], and compared to pixel-oriented projection is not fixed to one position. Typical charts to this category are line charts, bar charts, scatter plots and pie charts. The scatter plot is convenient to graphically represent and analyse time-series data, and to examine the correlation among different air pollutants. Such plots are simple to generate generate with libraries in python, such as matplotlib[1] and plotly [2]. It is possible

[1] www.matplotlib.org/,site loaded 16.5.2020
[2] https://plotly.com, site loaded 16.5.2020

to visualise up to four dimensions with a geometric projection, by using a color on the pixel as the fourth dimension. Some examples are seen in Figure

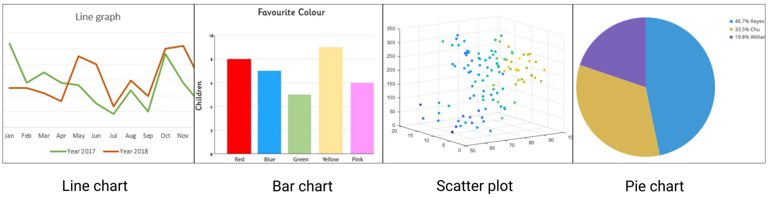


Figure 3.4: Geometric projection examples.

3.5.3 Icon-based visualisation

In icon based visualisation multidimensional data are represented with help of icons. Two popular icon-based methods are Stick figures and Chernoff faces [39]. Chernoff faces represent trends in the data by using a carton human face. Values of the dimensions are represented with components of a face, such as the size, shape, orientation and placement of eyes, month and nose. An example of an icon based visualisation can be seen in Figure 3.5.

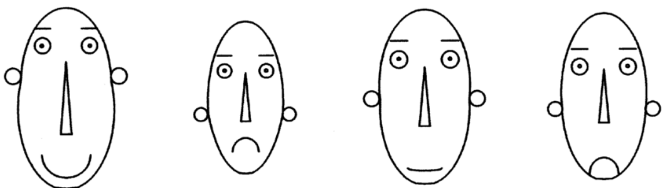


Figure 3.5: Example of Chernoff faces in an icon based visualisation. Image courtesy [38].

3.5.4 Hierarchical Projection

In a hierarchical projection the dimensions are partitioned into subset and visualised. Examples of hierarchical projection could be an organizational chart, where the membership relation between the different items are described. Another example could be a country that have multiple regions with multiple cities, which can be described as a hierarchical view. Hierarchical data can be visualised as a treemap, as seen in Figure 3.6

Figure 3.6: Example of a treemap. Image courtecy:[8]

3.5.5 Graph-based Projection

This modern visualisation technique is used to visualise large amounts of complex data and relations. For example contain a social network huge amounts of nonnumeric data, generated by e.g when users tag various items, such as a picture. Statistics of user generated tags can then be visualised by a tag cloud. An example of a tag cloud can be seen in Figure

Figure 3.7: Example of a tag cloud

3.6 Remote sensing and air quality visualisation

The literature on chemical structure and remote sensing contribute to the work of air pollution analysis. Satellite remote sensing has become a valuable tool in China to map the $PM_{2.5}$ spatial distribution and is useful in areas where ground-based measurement stations are insufficient [67]. Another benefit is that it provides the ability to get homogeneous views of large areas in single snap-shoots. However, challenging calibration and data processing is executed with professional software and can not be easily understood or shared with the general public.

When it comes to international services to visualise and monitor air quality, Plume by Plume Labs and AirVisual by IQAir are two prominent platforms to get some inspiration. Both Plume and AirVisual display the air quality on a map according to a specific air quality index. With global coverage, they use data from reliable public ground-based measurement stations, satellite aerosol monitoring, as well as data from crowd-sourced micro-sensors. Future predictions for weather and air quality is presented in both platforms, but the map displaying the information was different. AirVisual uses a fine resolution heat map to illustrate that air pollution intensity, while Plume map the colour to the nearest road in a street-by-street map. When researching these two applications, valuable information was collected. For example, simple and intuitive design was essential to get an overview of the local air quality quickly, and information about air quality data sources to build trust in the platform. They also suggested actions the user could perform, such as taking the baby for a walk or cycling outdoor. IQAir has recently made a collaboration with the UN Environment Programme (UNEP) and created the Urban Air Action Platform - A world map to empower governments to improve policies and allow citizens to make informed health choices and demand action from their governments [7].

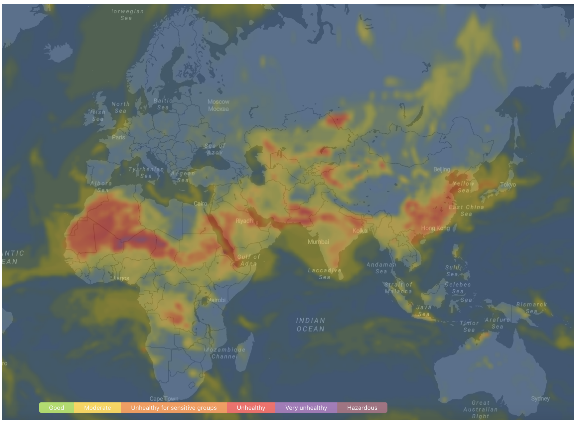


Figure 3.8: The screenshot illustrates PM 2.5 26. May 2020. Notice the dusty red areas from the desert in North Africa and unhealthy values around populated cities in India and China.

3.7 Data

Data represents the bridge that links sensors and the physical world together, [37]. Card et al. [17] describe the road map of data visualisation in four steps: raw data, data tables, visual structures and lastly views. The raw data is the unpolished data that is directly received from the data source. One way to distinguish data is by the value. According to Card et al. [18] data can either be

- Nominal (only $=$ or $\neq$ to other values).
- Ordered (obeys a ordered relation).
- Quantitative (numeric range or value).

The next step is when the raw data is transformed into data tables. This can change how the information is stored, for example with sorting, converting, combining of data or adding timestamp [17]. Further, the data is mapped to visual structures. The last step covers user interaction to view specific data ranges or change graphical parameters such as position, scale and clipping.

It is vital to evaluate the quality of the data before applying any analytic tools, so that wrong conclusion is not made based on errors in the data [61]. Improper data can cause biased analytics. Some typical reasons for improper data quality are invalid, inconsistent or missing data [25].

3.8 Low-cost measuring devices

Citizen science initiatives, such as Sensor.Community, that focus on air quality generally use low-cost sensors to measure the concentration of different pollutants. Low-cost, in this context, means a sensor system that cost less than 500 EUR including housing, data storage etc, which has a significantly lower price than official reference equipment. The price often depends on the quality of the electronics and housing, and also the extended services such as web visualisation and user support. This section provides an overview of the main types of devices currently available on the market and describe the different pros and cons of each type.

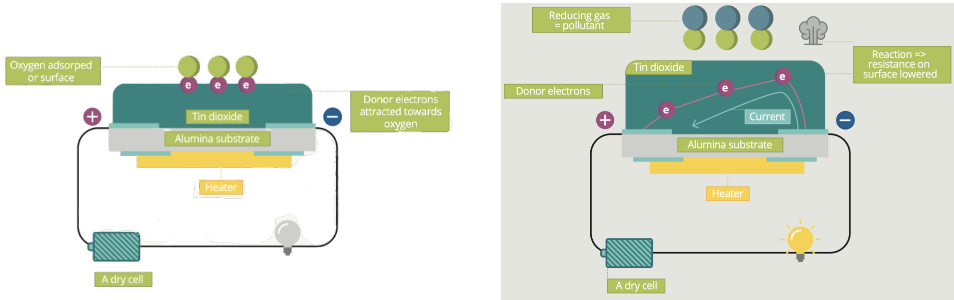
3.8.1 Passive air samplers

Passive samplers are often refereed to as diffusion tubes, which are small tubes containing reactive substances that absorb and accumulate air pollutants. These low-cost measurement devices are easy to use and can be placed in almost any location. Passive samplers are usually used for measuring the influence of NO_2 emissions from road traffic and benzene (C_6H_6) levels in ambient air. The EU Ambient Air Quality Directive [23] requires all member states to monitor these pollutants. The most significant downside of this type of sensor is the relatively long sampling period (typically four weeks) before the devices can be analysed; hence they can not provide readings in "real-time" on local air quality. The cost of one passive sampling unit, including handling and analysis, is 50 Euro (Alena Bartonova, NILU). A passive sampler mounted on a light post in Berlin can be seen in Figure 3.9.

Figure 3.9: Passive sampler near Brückenstraße in Berlin to measure NO_2 levels. Image courtesy: Paul Herenz, Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin [41]

3.8.2 Gas sensors

A typical type of gas sensor to measure gaseous air pollutants are metal-oxide sensors. Pollutants in the air react with the metal in the sensor and change its resistance, which allows current to run freely through the sensor. A schematic overview of the sensor functionality is seen in Figure 3.10. The amount of current is correlated with the pollutant concentration, and depending on the metal catalyst, the user can measure NO_2, O_3 and CO [41]. A disadvantage with metal sensors is that their response is limited to a high concentration of the target pollutant, and they can suffer from interference if other non-target pollutants are present in the air. Furthermore, gas sensors can gradually reduce their performance over time, and therefore be problematic for long measurement periods, such as a year. They are also vulnerable to variations in temperature and humidity.



(a) Clean air **(b)** Polluted air

Figure 3.10: A schematic overview of how metal oxide sensors work in clean and polluted air. Figure courtesy: FIGARO Engineering Inc., Japan [41]

Another type of gas sensors is electrochemical sensors. They are built around electrodes in contact with an electrolyte. When the electrode reacts with a gas molecule, such as NO_2, a sensing electrode in the liquid will generate a small current proportional to the gas concentration. Similar to metal-oxide sensors, the electrochemical sensors are sensitive to variations in temperature and relative humidity, and also suffer from inference from non-targeted gases near the sensor [20].

3.8.3 Particle sensors

It is common to use an optical particle sensor to measure particulate matter in the atmosphere. Air enters the sensor via a small fan or by heating an element and is illuminated with a light source. The particles in the air stream cause scattering light to hit a detector, providing a particle concentration proportional to the intensity of the scattered light. Based on signal amplitudes, the sensor counts the particulate matter distribution in selected bins. In comparison, official air quality reference instruments often use a 'gravimetric' method (particles collected on a filter) to measure the PM concentration, which is finally analysed in a laboratory. A low-cost PM-sensors also suffer from the influence of high relative humidity levels, as they do not have the same system to dry the inlet air.

Also, a correct calibration procedure of the sensor is essential, since particulate matter has characteristics such as colour and shape that influence the readings.

From the properties derived above is therefore the low-cost particulate matter sensors considered much more uncertain than official reference instruments [41].

3.9 Pollutants

Information about the most common airborne pollutants and where they typically originate from can be found in Table 3.2.

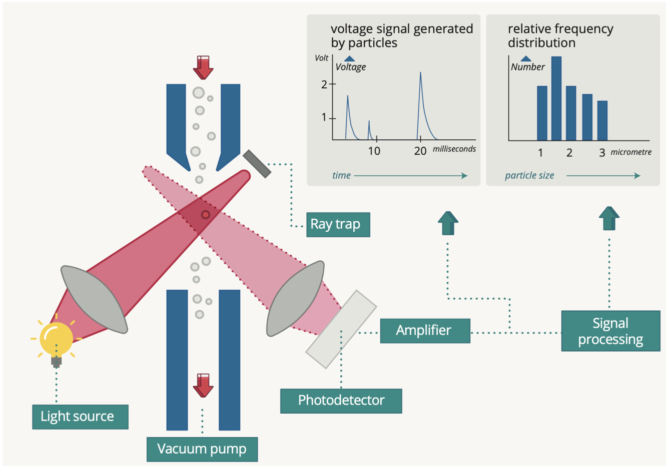


Figure 3.11: Schematic illustrating the technical design of an optical particle sensor. Image courtesy EEA [41]

Air pollution classes for particulate matter in Norway is categorised in four colour classes from green, yellow, red and indigo, corresponding to low, medium, high and very high levels respectively. An overview of the classes and their limit values can be found in Table 3.1.

Class	**Level**	**Health risk**	**Daily level** ($\mu g/m^3$)		**Hourly level** ($\mu g/m^3$)	
			PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$
	Low	Low	<30	<15	<60	<30
	Medium	Medium	30-50	15-25	60-120	30-50
	High	High	50-150	25-75	120-400	50-150
	Very High	Deadly	>150	>75	>400	>150

Table 3.1: Air Pollution classes for particulate matter in Norway given by the Ministry of Climate and Environment.

3.10 Mechanistic vs data-driven modelling

Models can be designed to estimate, predict and project the future. Missing data, or discontinuity in the data is often an obstacle in time series analysis and prediction. Therefore, estimating air quality can be useful in situations where the data is missing. Prediction models allow us to estimate what will occur in the future based on the past history, often to some degree of probability and with the assumption that future changes are similar to today's level and will not have significant influence. In other words, a prediction is most dependent on initial conditions - the current situation from where we predict the change.

A short-range prediction of particulate matter and atmospheric gasses is especially of in-

Type	Information
CO	Carbon monoxide, from combustion of wood, coal and gas. Product of incomplete combustion
CO2	Carbon dioxide is an essential element in the nature. Deforestation and burning of fossil fuel contributes to high levels of CO2 emission. The gas traps heat in the atmosphere and contribute to climate changes.
NOx	Nitrogene oxides are emitted as nitrogen monoxide in combustion of fossil fuel, from transportation and industry. It reacts with ozone or radicals in the atmosphere and transforms into nitrogen dioxide.
SOx	Sulfur oxides come mainly from industrial activities of processing materials containing sulfur or burning of coal, oil and gas that contains sulfur.
PM	Particulate matter is the generic term for pollutants consisting of complex and varying mixture of particles $PM_{2.5}$ and PM_{10} denotes the diameter of the matter less than 2.5 microns and 10 microns respectively.
O3	Ozone is formed when pollutants from cars, power plants and chemical plants react in presence of sunlight. The greenhouse gas is created by chemical reactions between nitrogen oxides and volatile organic compounds.
VOC	Volatile organic compounds can be found in household products, like paint and aerosol cans. The compounds are volatile since it can easily turn from solids into vapors or gases. Contributes to air pollution and serious health conditions.

Table 3.2: The most important types of pollutants.

terest in order to detect spikes and anomalies so that people vulnerable to air pollution, such as asthmatics can avoid the risk of exposure. This can also open opportunities to offer free public transportation or restriction of diesel cars, to reduce the commuting traffic on a day with high predicted values [54]. Models capable of long-range prediction is also of interest in situations in order to evaluate the long term effects of different air quality management scenarios. In Trondheim, one such scenario could be to see the effects of street cleaning, to reduce the amount of particulate matter. Most PM models are designed to predict short-range hourly mean or maximum daily concentrations one day ahead [64].

It is normal to differ between mechanistic and data-driven modelling. Mechanistic models have a solid foundation based on physics and require theoretical information to simulate a process, using mathematical equations on transportation and transformation of substances. It is impossible to model exactly the nature, despite a large variety of input data. Therefore approximations have to be made with model modifications, and missing information is either estimated or simplified. It often begins with a meteorological forecasting to predict the conditions of the atmosphere, contributing to errors and uncertainties in the model.

Data-driven models have gained traction in the last decade, and a vast majority of models originate from statistical modelling and machine learning. These models tend to be good

Mechanistic modeling	
Pro	*Con*
Solid foundation based on physics	Difficult to assimilate very long term historical data into the computational models
Errors or uncertainties can be bounded and estimated	Computationally expensive
Less susceptible to bias	Sensitive to numerical instability
Generalizes well to new problems with similar physics	

Data driven modeling	
Pro	*Con*
Takes into account long term historical data and experiences	Mostly black-boxes
A trained model is very stable and efficient for making predictions	Not possible to bound errors / uncertainties
	Bias in data is reflected in the model prediction
	Poor generalization on unseen problems

Table 3.3: Pros and cons of mechanistic and data driven modelling.

in modelling highly non-linear functions, and once trained they can generalize well to unseen problems of similar characteristics. Machine learning algorithms learn from the data they are trained on, finding patterns that are not necessarily obvious in the data. A data-driven PM model uses ground-level sensor data and is dependent on measurement of pollutants and meteorological states, accurate to a small area around the monitoring station. In comparison to mechanistic modelling, it does not aim to replicate the physical or chemical processes involved in generation, transportation and dissipation of particulate matter. Table 3.3 illustrates the pros an cons of mechanistic and data-driven modeling.

3.11 Spatio-temporal Data Analysis

Spatio-temporal data analysis is a growing research area today, greatly motivated with the development of powerful graphical processing units (GPUs). The phrase Spatio-temporal or Spatial-temporal, where spatial refers to space and temporal refers to time, is used in data analysis when data is collected across space and time.
Applications for Spatio-temporal data analysis include the study of meteorology, biology, transportation and more. Spatio-temporal data visualisation and analysis can be challeng-

ing since space have unlimited directions - up, down and sideways, while time can only go forward. Not only is the process of combining space and time complex, but it can also produce different result depending on how space is defined. The data granularity - the level of detail of the data could vary from sub-meter level to zip-code based or across states. Time could also provide conflicting results depending on whether it is presented in seconds, hours, days or years.

3.12 Models

3.12.1 uEMEP Model

Today, there exists a national online Air Quality forecasting platform[3] that presents current air quality levels from measurement stations, as well as hourly prediction around in Norway. The platform is a joint project between the Norwegian Environment Agency (Miljødirektoratet), the Norwegian Public Roads Administration (Statens vegvesen) and the Norwegian Meteorological Institute (Metrologisk institutt). The local air quality forecast applied to the platform is an urban Gaussian dispersion model, called the uEMEP model, and is based on the long-range transport model model, the European Monitoring and Evaluation Programme (EMEP) model. It calculates the concentration in a target grid from any particular emission grid. Later the uEMEP sub-grid concentrations are combined with the EMEP grid concentration to include local and non-local sources and prevent double-counting, as seen in Figure 3.12

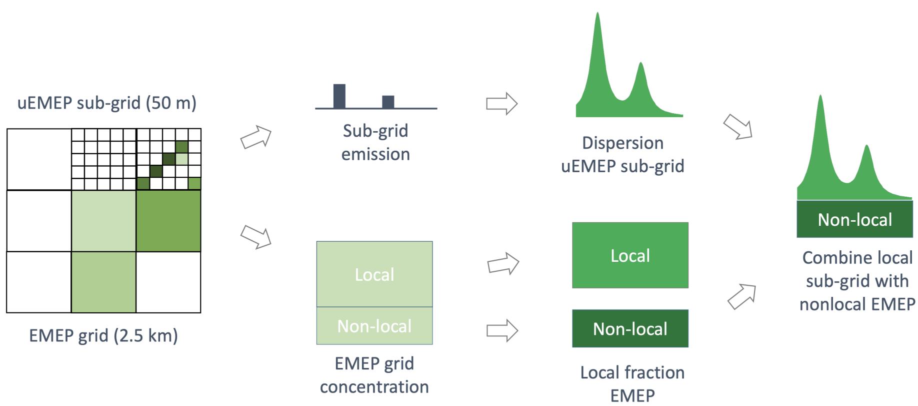
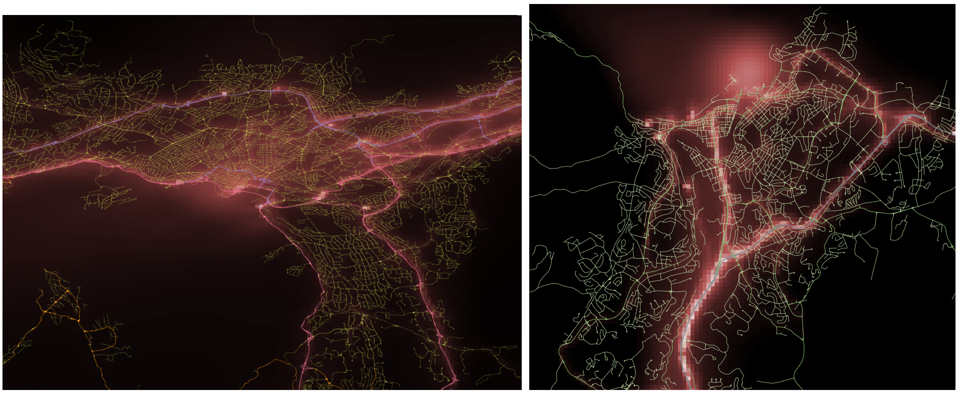


Figure 3.12: Illustration of how uEMEP sub-grids are combined with EMEP grids. Image courtesy: The Norwegian Research Council [15]

The model outputs a 2-day hourly forecast for the pollutants PM_{10}, $PM_{2.5}$, NO_2 and O_3. The model also gives an indication of local emission sources for each pollutant from:

- Traffic exhaust

[3] https://luftkvalitet.miljostatus.no/



(a) Oslo **(b)** Trondheim

Figure 3.13: Visualisation of NO_2 levels in Oslo and Trondheim using the EPISODE model.

- Traffic non-exhaust
- Shipping emissions
- Residential wood burning emissions
- Industrial emissions

To validate the model and the forecast prediction measurements from stationary sensors around in Norway were used. These measurements stations are provided by the Norwegian Institute for Air Research (NILU).

There is a growing interest in new generation plume models in Europe, such as the EPISODE model, and we expect that new models will slowly replace the old generation Gaussian plume models in air pollution dispersion calculations [49].

3.12.2 EPISODE model

The EPISODE model is an Eulerian urban dispersion model, developed by researchers in Norway and Germany [31] to support planning and air quality management in the Nordics. In an Eulerian model, the cordinate system fixed to the ground is used. The model consist of an Eulerian 3D grid model (consider vertical and horizontal coordinate axis) with embedded sub-grid dispersion models for diffusion from line (e.g roads) and point sources (e.g wood burner stoves). The model is suitable for assessment of annual mean and hourly NO2 concentrations. Figure 3.13 display the NO_2 lelvels in Oslo and Trondheim, and was developed with dataset from NILU.

3.13 Situation in Trondheim

3.13.1 Meteorology and Topology

It is shown that air quality levels have substantial local variations and change with the weather, size of buildings and amount of traffic [4]. Trondheim is a city located where the river Nidelva meets the Trondheim Fjord, with an oceanic and humid climate. The coastal climate is also very windy and cause short winter months with dry polluted air.e short. The elevation map in Figure 3.14 explain the topography in Trondheim. The topography is favorable to prevent air pollution, since there is no canyon profile that may trap and gather the pollutants.

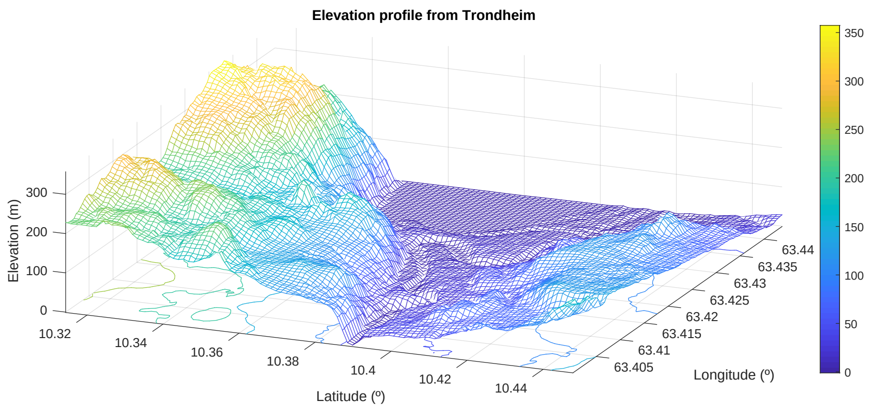


Figure 3.14: A elevation map from Trondheim. Parts of Geitfjellet and Våttakammen mountain with 286 meter above sea level can be seen in the left side of the map

3.13.2 Road cleaning

Trondheim municipality started with a strict road cleaning policy in 2013. To reduce the amount of airborne particles. From 1st of January 2020, a national ban of all oil heaters was introduced, and it is expected that this change will slightly reduce the backgrounds levels in urban areas. A major source to airborne particulate matter is traffic, and the levels rise during winter months when cars use winter tires and cause wear and tear on the roads.

A line plot of air quality data from the NILU measurement station near Elgeseter street is displayed in Figure 3.15. We can clearly see a significant difference in PM_{10} levels between the winter and spring months. Due to the corona pandemic, a national shutdown of schools combined with travel restrictions was enforced from 12th of March (marked with a green line). These restrictions reduced the number of cars and busses on the road, and we notice a period with stable readings. From the beginning of April to Mid-May street cleaning and dust removal were performed on the main roads around Trondheim, and this further reduced the daily PM_{10} levels.

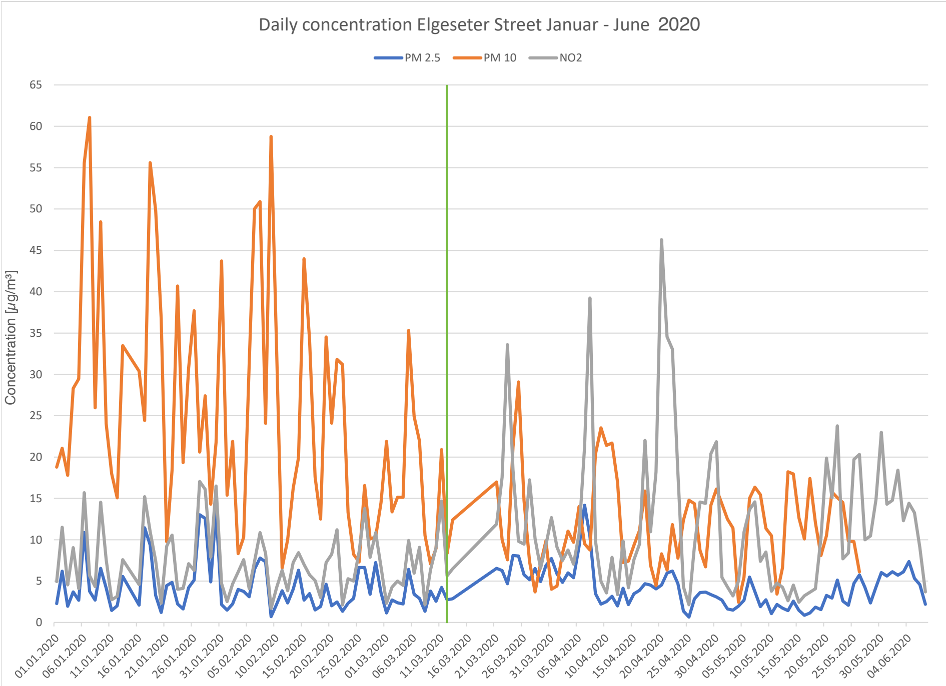


Figure 3.15: Line plot with the daily mean concentration for $PM_{2.5}$, PM_{10}, and NO_2 from Elgeseter station (NILU). The 12th of March when Norway closed down due to the corona-pandemic is marked in green color.

3.14 Ensure quality and reliability

A challenge with crowd sourced air quality projects is to ensure the quality and reliability from the low-cost measurement device. Data quality is in this setting, is referred to the the performance of the sensor system in terms of accuracy and stability when compared with a high-end reference instrument. Lewis et al. [41] consider a number of parameters to define the performance:

- Sensitivity
- Selectivity
- Temporal resolution
- Reproducibility

A sensitive sensor can capture both high and low concentrations. For example, is the HPM Series particle sensor used in our prototype revision 1, is originally designed for indoor air quality applications with limited particle size (0.3 μm - 5 μm), and struggle to capture very high concentrations. Selectivity defines how good the sensor works under interference from environmental changes and other pollutants. For example may electrochemical sensors be sensitive to changes in temperature, relative humidity and pressure, especially when operating in the lower limit of their sensing spectrum [12]. Temporal resolution tells how often the sensor provides measurements, and reproducibility explains the consistency in the sensor over time.

Recent scientific literature shows that there are some trade-offs when using a low-cost sensor, rather than a professional reference method. Smaller and cheaper units tend to be less precise, less sensitive and less chemical selective to the compound of interest. This may be because they use different measurement technique to reference methods, or that they are essentially limited, for example through shorter optical characteristics for absorption (a common measurement technique for particulate matter compounds). They also may report the measurement readings in different values (e.g. voltage or particle number) than the reference station, or that conversion to meaningful units may not be direct.

The Sensor.Community(2020)[4] acknowledges the challenge with data accuracy from portable, low-cost sensors. A comparison with advanced optical measurement stations has shown that the results are acceptable during typical conditions when humidity is in the range of 20-50 % and particulate matter (PM10) concentrations are below 20 μg/m^3 [16]. However, during times with high humidity, for example, when it was foggy, the sensors could give incorrect readings. The Sensor.Community is therefore looking for algorithms to reduce the impact of high-humidity on particulate matter readings.

[4] https://sensor.community/en/ (site loaded 1.6.2020)

Chapter 4

Methodology

Research methods can be broadly divided into two methods, qualitative or quantitative, and which one to select depends on the objective of the study. Qualitative research is any which does not involve numerical data and may be studies concerned with soft values such as human behaviour, which focus on answering why people act the way they do. In comparison, a quantitative research is used when the information is measurable (e.g. numerical data), which can be analysed using mathematical or statistical methods.

During the research with this thesis, several online platforms were developed to showcase a visualisation of air quality in 2D-, 3D-heat map, and as a dashboard with historical time-series line plot. Lastly, video-interviews were held on Zoom with selected individuals from each user group defined below, to evaluate the three platforms.

4.1 Method model

This study consisted of an initial phase, followed by a theoretical study, implementation and evaluation phase. A graphical structure of the stages is illustrated in Figure 4.1

During the initial phase, the objective of the study was determined, and the research questions were developed. Inspiration from previous works related to air pollution at the university was helpful to learn from pitfalls and to narrow down the problem. In the theoretical study phase visualization tools and projects related to low-cost air quality units was examined. Implementation and evaluation were two following steps with several iterations. Field testing of the sensor platform from Exploratory Engineering was part of the implementation phase and included walking, biking and bus driving. Collection of empirical data was conducted in the evaluation phase during interviews with three individuals from each user group, in total 9 participants.

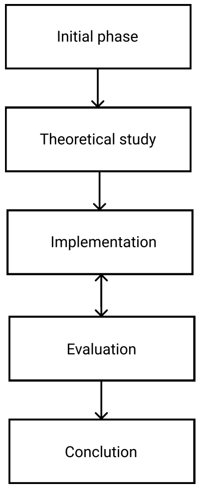


Figure 4.1: Method model

4.2 User Groups

We define the following three user groups in this thesis, specially interested in air quality.

- **User group 1:** Citizens
- **User group 2:** Policy makers
- **User group 3:** Researchers

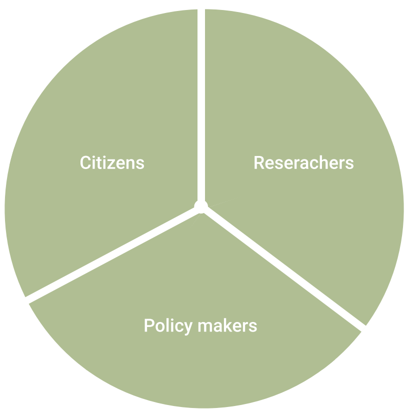


Figure 4.2: User groups

User group 1 Citizen are children, elderly and individuals at risk. This could be smokers and people with lung diseases, such as asthma and chronic bronchitis. The individuals of a city is also a contributor to air pollution through polluting acts such as the use of cars and wood burners urban areas. A study in Scotland of Air Pollution and Health from Hyland et al. [34] found a perceived lack of understanding amongst the public about the health risks associated with air pollution. On the other hand, recent studies from the European Environment Agency (EEA) have shown that people's perception of air pollution and the associated risks has grown significantly over the late years, often informed by media publicity, or local campaigns led by non-governmental organisations (NGOs). In some countries, we have also seen a trend where groups of exposed citizens have taken authorities to court over air quality concern. The EEA report "Assessing air quality through citizen science" shows that citizen science initiatives can produce useful information about local air quality. Such information could be crowdsourced using low-cost sensors, to improve official air quality models estimating air pollution, or to identify proper actions to improve air quality [46].

User group 2 Policy makers are municipalities, politicians and national road authorities. They have the responsibility to make sure that the air quality is within safe limit values, given by national guidelines. This user group is also responsible for monitoring pollutant work, e.g. outdoor digging activity, and take the required action to reduce the spread according to the Pollution Control Act. The policy makers have close communication with the citizens through media channels, to address the issue of air pollution or change public behaviour, through intensives such as switching from driving to cycling or walking.

User group 3 Researcher this group consist of scientists from the Norwegian Meteorological Institute, the Norwegian Institute for Air Research (NILU) and researchers at NTNU. This user group is responsible for providing scientific reports, conducting experiments and maintain the infrastructure of monitoring stations around in Norway. They have all a common goal to provide information about air quality and the raise public awareness around the pollution problem.

4.3 Data collection

To perform a spatio-temporal data analysis with data from several input sources, we need a clear understanding of what we want to measure. Design of experiments (DOE) is a systematic method to determine the relationship between factors that affect the process and the output. In other words, we use it to find cause-and-effect relationships between input and output.

The most commonly used terms in DOE include:

- *Controllable input factors:* Input parameters that can be modified in an experiment or process.
- *Uncontrollable input factors:* Input parameters that cannot be changed.
- *Response, output measures:* Elements of the process that give the desired output or effects.
- *Hypothesis testing:* A tool to determine significant factors using statistical methods. The testing is done at a level of significance, based on a probability.

- *Blocking and replication:* This is an experimental technique to avoid undesired variations in the experiment. This could be to conduct all experiments with the same equipment to keep the same level of error in the experiment. Replication means to run the same experiment more than once, in order to discover the randomness in the error that could be part of the process.

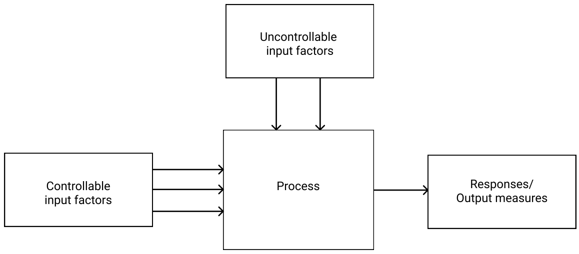


Figure 4.3: Diagram with process factors and responses

An overview of available input sources to analyse air pollution in Trondheim:

- Air pollution sensors (NILU)
- Micro sensors (Telenor EE)
- Weather data (YR)
- Wood burner dataset (Trondhiem Kommune)
- Traffic count (Statens Vegvensen)
- Construction sites

The Norwegian Institute for Air Research (NILU) is the official manger of reference stations for air quality monitoring in Norway, and offers research, services and advice to public administration and industry. The monitoring activity is linked to several different international programs and research infrastructures, such as the European Monitoring and Evaluation Programme (EMEP) [52]. NILU has three reference monitoring stations in Trondheim at Trondheim Torg (Municipality building), Elgeseter street, and Tiller near E6. The two latter are mounted near heavily trafficked roads, while the first one is mounted to capture more of the residential background pollution. A table with their locations can be found in Appendix A.1 in Table A.1. NILU offer a public API to download historical air quality data of CO, NO, NO_2, O_3 and particulate matter[1].

In addition to the NILU sensors, Exploratory Engineering has developed in collaboration with Telenor a set of mobile, low-cost air quality sensors. They are able to monitor temperature, humidity and air quality, and comes with integrated GPS for location data. Such types of sensors make it possible to build dense networks, and when combined with data from reference monitoring stations and model calculations, it can provide air quality data with very high spatial resolution.

[1]https://api.nilu.no/ (site loaded 15.5.2020)

Evaluation and validation of measurements are essential for accurate data from low-cost sensors. The procedure will not be covered in this thesis, but we stress the importance of including it in a full-scale system. Sensors which are able to measure gas and particles from air pollution can be sensitive to weather conditions (e.g. wind, variations in temperature and humidity) or when differentiating between several pollutants [53].

The Norwegian Meteorological Institute and the Norwegian Broadcasting (MET) Corporating (NRK) provide an online weather service called Yr. Among the biggest weather service providers in Europe, with more than a million users every week. Similar to NILU they also provide an open API to download historical weather data, including humidity, temperature, wind and wind direction [66].

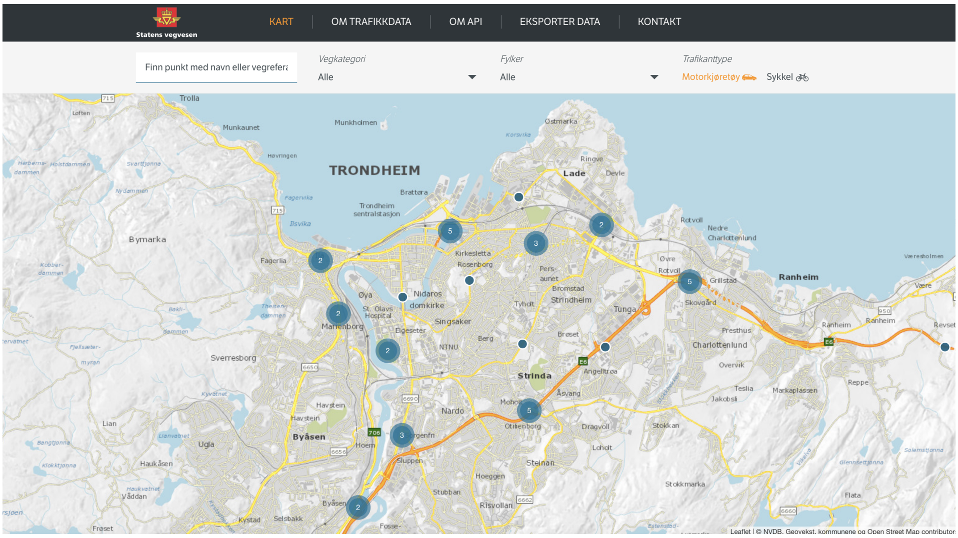


Figure 4.4: A screenshot from The Norwegian Road Authority traffic counter dashboard. Currently is 37 stations monitoring the traffic in and out of Trondheim

The Norwegian Road Authority (Statens Vegvesen) provide a traffic counter data base in Norway[2]. Their mission is to provide accurate and quality controlled data about the flow of vehicles on the road. With inductive counters on selected roads, they can detect speed, length and vehicle class and distance between vehicles. All main roads going in and out of Trondheim have a traffic counter, and the data is publicly available from the dashboard and online API, aggregated with two hours delay. A figure of the measuring location and how the traffic counter works can be seen in Figure 4.4 and Figure 4.5 respectively.

Construction sites can be a significant source of airborne pollution and can carry over long distances over a long period of time. Various activities such as land clearing, demolition, burning and operation of diesel engines contribute to air pollution. In New Delhi 30 per cent of air pollution is caused due to dust from construction sites [60].

[2]https://www.vegvesen.no/trafikkdata/ (site loaded 22.07.2020)

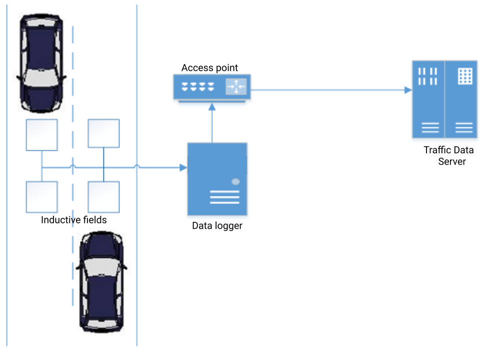


Figure 4.5: The figure illustrates how the traffic counter register the vehicles and transfer the data in real time. Image courtesy Statens vegvesen

An online platform called **trondheim.gravearbeider.no** provides an interactive overview of all reported construction sites, both ongoing and planned, in Trondheim. A screenshot of all ongoing ground related constructions (in May 2020) can be seen in Figure 4.6

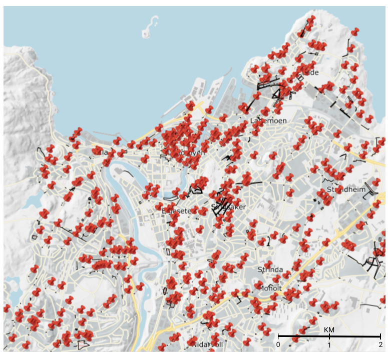


Figure 4.6: The map gives an overview of construction sites where ground work is taking place in Trondheim

Another source of airborne pollution in Norway is residential wood burners. Since the electricity produced from hydropower is the primary source of heating are renewable, wood-burning stoves are the second most important source of heating. The effect of this is significant emissions of particulate matter (PM) and other compounds with negative effects on our health [45].

Figure 4.7 displays a density heat map with the distribution of residential wood burners in Trondheim. It is generated from a dataset given by Trondheim Municipality, and contain more than 50000 unique locations, about 2/3 of all registered residents in Trondheim.

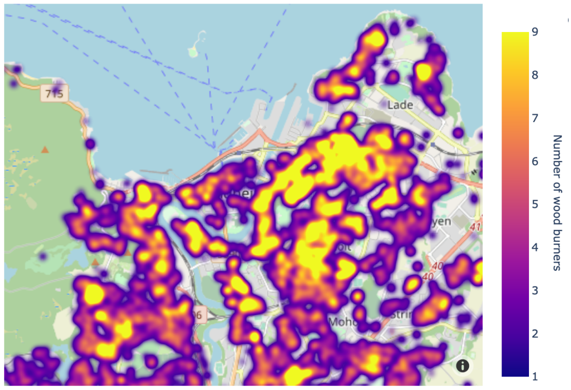


Figure 4.7: Density heat map of the residents with wood burner in Trondheim

4.3.1 Micro Air Quality sensors

To conduct a similar drive-by sensing experiment, we use small micro air quality sensors developed by Exploratory Engineering in Trondheim. Exploratory Engineering (EE) is an R&D team at Telenor, and develop hardware prototypes, and software for the Internet of Things (IoT) enabled devices. Both stationary and bus mounted sensors were used in this experiment.

Sensor platform	Rev. 1	Rev. 2
GPS	Yes	Yes
Temperature	Yes	Yes
Humidity	Yes	Yes
Particulate matter	$PM_{2.5}$, PM_{10}	PM_1, $PM_{2.5}$, PM_{10}
Chemical pollutants	CO_2	CO_2, NO_2, NO, O_3

Table 4.1: A list of the different sensors used in revision 1 and 2

The first prototype board, seen in Figure 5.1a, was originally developed for a research project in Tromsø in 2017 with the aim to be mounted on bus rooftops. It consisted of a circuit board with sensors and a NB-IoT communication modem. The sensors monitor and report levels of temperature, humidity, $PM_{2.5}$, PM_{10} and CO_2 equivalent predictions, as well as GPS coordinates for localization of the sensor data[3]. The particle sensor, a Honeywell HPM Series (32322550), is a laser-based PM sensor that detects and count particles using light scattering technology.

The second prototype board seen in Figure 5.1b was an improved version of its predecessor with ability to detect more chemical pollutants in addition to CO_2, such as NO_2, NO and O_3. A general challenge with chemical sensors is stability, since the performance and sensitivity degrade over time, which in turn limit the operating time before re-calibration

[3]https://blog.exploratory.engineering/post/where-the-air-is-crisp/ (site loaded 16.6.2020)

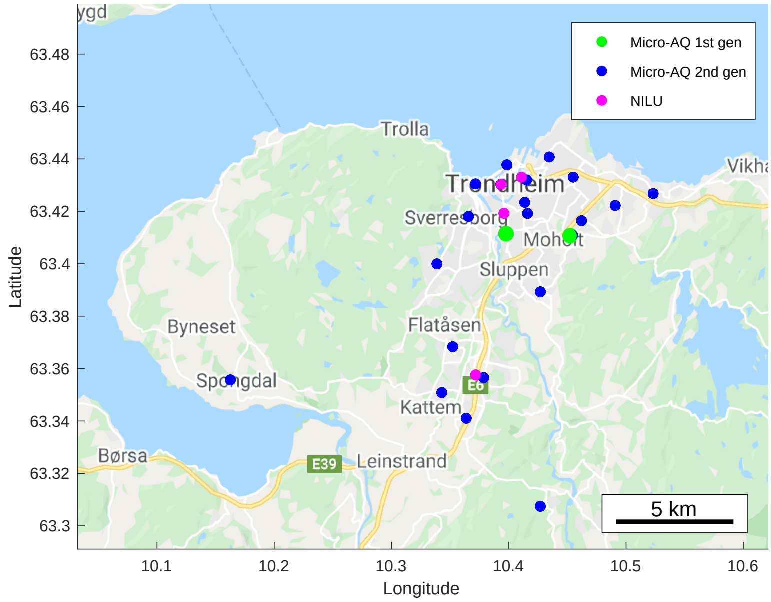


Figure 4.8: Placement of the micro-sensors 1st and 2nd generation. NILU reference stations are marked in purple.

is required [12]. The new prototype also features an upgraded particle sensor from Alphasense (OPC-N3), that is able to differentiate between PM_1, $PM_{2.5}$ and PM_{10} particle sizes. A feature overview is given in Table 4.1. The sensor measures particle counts in 24 bins from 0.35 micrometre to 40 micrometre by illuminating one particle at the time with a laser, and measure the intensity of the light scattered. The amount of the light scattered is a function of the particle size, which is calibrated using a proprietary algorithm from Alphasense. This sensor is similar to the sensor used in the City Scanner project from MIT [10]. In a collaboration project between Telenor Research and Trondheim Municipality, the air quality prototypes will be deployed on selected schools and kinder gardens around in the city this summer. The different geographical locations can be seen with blue marks on the map in Figure 4.8, or in Table A.3 in Appendix A.1.

4.4 Architecture

Raw sensor data from the device included temperature, humidity, CO_2, $PM_{2.5}$ and PM_{10} was broadcasted via Narrow Band (NB-IoT) to a server platform hosted by Telenor called Managed IoT Cloud. The payload from the sensor was encoded as Base64 on the device, to represent both binary and non-binary data as a string[4].

To be able to visualise data points in a Grafana Dashboard, it had to be stored in an Influx Database. This was made possible with a Thing API from the Managed IoT Cloud,

[4]https://blog.exploratory.engineering/post/making-sense-out-of-nonsense/ (site loaded 20.6.2020)

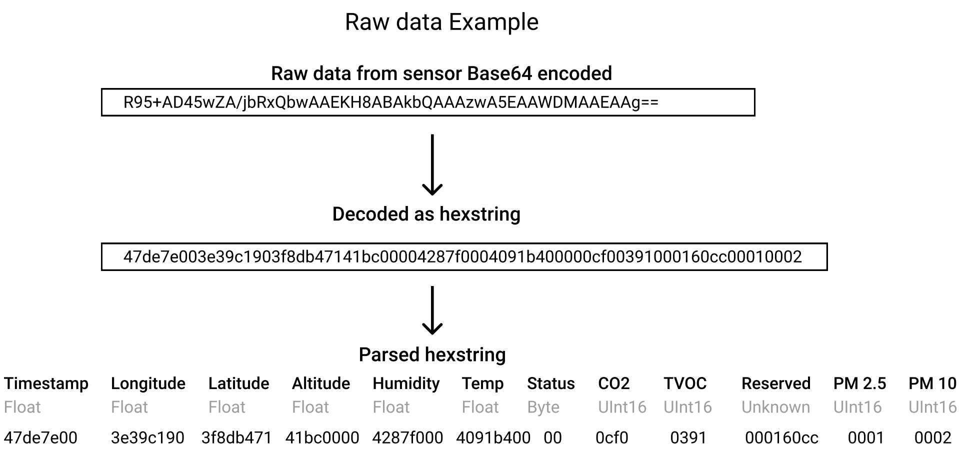


Figure 4.9: This example illustrates how the incoming data to the Telenor server is parsed

via a MQTT messaging protocol. Message Queuing Telemetry Transport (MQTT) is a lightweight publish/subscribe protocol that allows the Managed IoT Cloud to relay incoming messages encrypted to a broker. A client on the Influx server side connect to the same broker, decrypt the messages via public-key authentication and store the messages in the database. The code to handle this communication was written in Python and can be found in Appendix A.3. Figure 4.9 illustrates an example of how the raw data is parsed in the Managed IoT Cloud. Note that the Total Volatile Organic Compound (TVOC) is also reported from the sensor. TVOC is often used to measure organic chemicals in the air, such as Benzene, Toluene and Formaldehyde that evaporate at low temperatures [13]. It can originate from painting, furniture and plastic products, and often adds up indoor in buildings with poor ventilation. Since we focus on outdoor air quality in this thesis, the TVOC readings will not be considered in the visualisation.

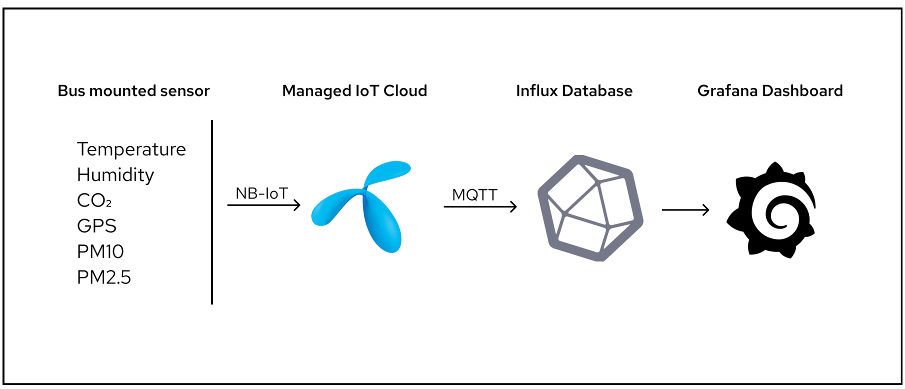


Figure 4.10: Micro Air-Quality sensor setup

The last step in our architecture pipeline from Figure 4.10 is the Grafana Dashboard. Grafana is an open-source visualisation and analytic software that allows the user to query, visualise and explore data stored in a time-series database, such as Influx. They provide useful tools to create beautiful graphs and dashboards, that can be shared for multiple users via an online portal [5]. Our dashboard was hosted in an instance from the DigitalOcean, a cloud infrastructure provider similar to Amazon Web Services, and can be accessed on **ntnu.chat**. Links to a demo video of the platform is available in Appendix A.2.

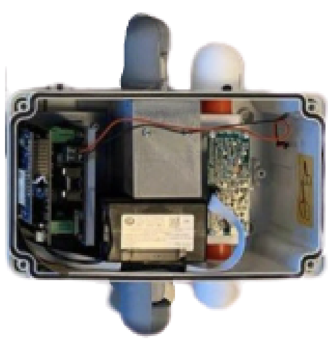
[5] https://grafana.com/docs/grafana/latest/getting-started/what-is-grafana/ (site loaded 12.6.2020)

Chapter 5

Experiment

In our experiment, three micro air quality prototypes from the first generation were selected to harvest data over a period of six days. Due to power supply challenges, only one sensor was mounted on the bus rooftop, and the other two sensors were placed on stationary positions near the weather station at Voll, and at Lerkendal Student village next to the heavily trafficked Elgeseter street. Including more micro-sensors in the experiment would be preferred, to get a larger sensor coverage in Trondheim, or to have multiple sensors on the same location and/or bus route to check for redundancy and result in similarity. Since the second generation sensors were not ready for deployment at the time of our testing, and the last batch of the first generation sensors was for out for repair or replacement, we were limited to three micro sensors. Images of the two stationary locations can be seen in Figure 5.2 and on the map in Figure 4.8 with green marker.

(a) AQ sensor rev. 1



(b) AQ sensor rev. 2

Figure 5.1: AQ revision 1. from 2017 and AQ revision 2 from 2020, upgraded with electrochemical sensors. Image courtesy: Hans Jørgen Grimstad, Exploratory Engineering

When the dashboard was developed, we took the sensor for a walk in Trondheim, to test the performance in cold winter temperatures. The current consumption was about 0.1 A per hour on average in continuous sending mode each minute, which corresponds to about eight days of use with a large-size power bank (20000 mAh capacity).

Tide AS is the largest bus company in Trondheim and operates the bus routes for AtB. They were helpful to facilitate the moving bus experiment and provided a city bus driving on line 13 and 14. The lines cover both trafficked roads and residential areas, over a driving length of 10.8 km and 10.3 km each. The duration of the bus experiment was constrained to the battery capacity since there was no external power outlet to power the sensor from the bus. A challenge we faced with the field-testing was the fact that a bus had to be available in the repair garage in order to climb the roof. Since it could go weeks before the same bus was back in the garage again, there was not an easy task to get the sensor down for battery replacement, once the experiment was started.

(a) Tide Bus

(b) Voll

(c) Lerkendal

Figure 5.2: Illustration of where the low-cost sensors were mounted.

5.1 Grafana Dashboard

A screenshot of the Grafana dashboard can be seen in Figure 6.1 in Chapter 6.1, and included a historical line chart and a corresponding map with geographical information for each of the three sensors in the experiment. A closer look and description of the key buttons can be seen in Figure 5.4 and Figure 5.3 respectively. Note the time selector in the top right corner, where the user could define the start and end time for the current view. The view was dynamically updated as new readings arrived. Navigation by selecting a closer section was also possible with a click-and-drag gesture in the line graph, or with the zoom buttons in the map view. The map marker colour threshold for PM_{10} and $PM_{2.5}$ values reflect the three first air pollution classes green, yellow and red from Table 3.1. The exact value to a data point could be seen by clicking it.

All sensor parameters were plotted in the same graph, as seen in the line chart in Figure 5.4 for the Lerkendal micro-sensor. This design selection was made to make it easy to compare e.g. CO_2 readings with particulate matter. A hover panel with raw values became visible when the user moved the cursor across the timeline. The labels were located under

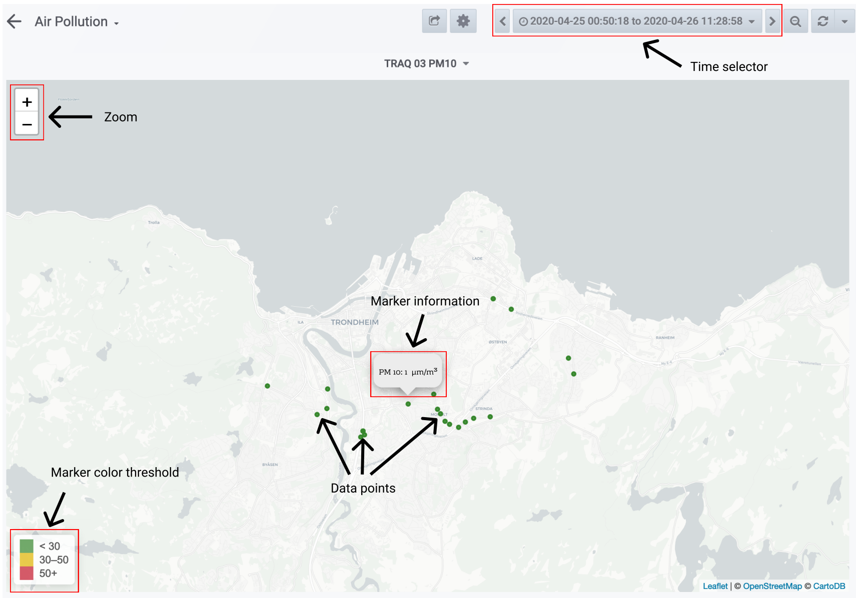


Figure 5.3: A screenshot of the map from the bus experiment with key dashboard information explained

the timeline and included colour and the average value for each parameter in the open window.

5.2 2D visualisation

A web application with a 2D map was made to visualise the readings from the experiment collected by the sensor. A screenshot from the application with the walking experiment performed on 12th of March in Trondheim can be seen in Figure 5.5. The data was fetched from the Managed IoT Cloud platform via the Things API and converted to a Geo-JSON format to be viewed in the application made with JavaScript and HTML. Listing 1 illustrates the Geo-JSON message format. The user can replay the route from the experiment with the play/pause button in the time data arrived. A click on the measurement would bring up a marker panel with detailed information of $PM_{2.5}$, PM_{10} and CO_2 levels. The colour of the markers in the view can be changed with the attribute selector buttons below the map.

5.3 3D-visualisation

Inspired from the work done by Dembski et al. (2020)[22], where they created an urban digital twin of Herrenberg in Germany, we wanted to visualise air pollution in a simulated 3D model of Trondheim. The 3D model itself was provided by Rambøll AS and Trond-

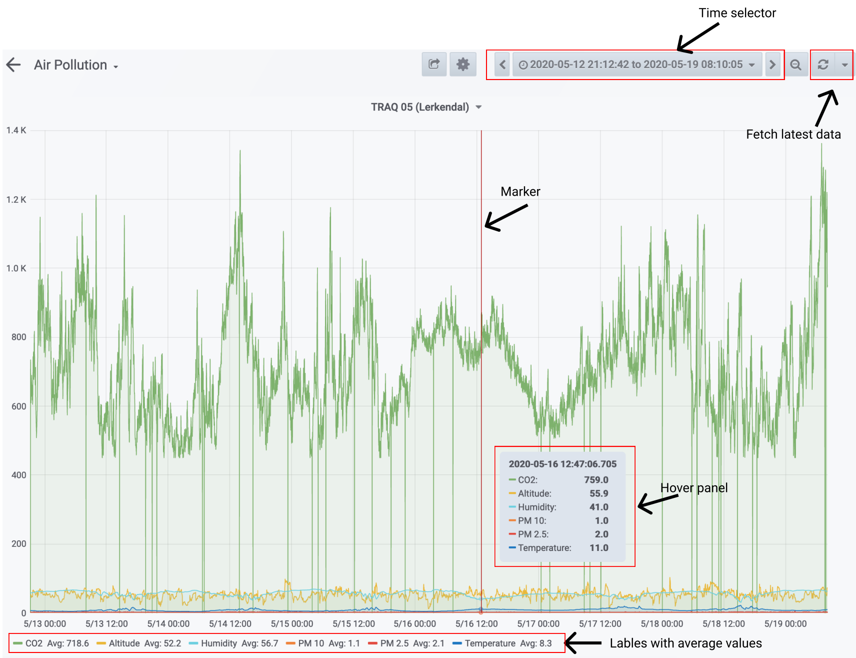


Figure 5.4: Historical time series display explained

heim municipality and implemented using the Unity Game Engine. Unity is the world's leading platform when developing games and simulated environments [3], and was suitable for the task of visualising air pollution.

To visualise the pollution particles similar to the Clean A/R project described in Section 2.2, Unity has a Particle System toolbox we experimented with. The toolbox allows us to simulate smoke and particles in the scene, and we can adjust how particles are generated and disappear. Particles can also be influenced by physical effects such as a gravity force and wind for a realistic feeling. Figure 5.7 illustrates how the particle system can be used to dissolve elements in the view with a sparkling effect.

Our initial idea was to map the Spatio-termporal data from the microsensor to the scene in the Unity simulator seen in Figure 5.6 as colourized particles, which was dynamically updated as new readings become available. Due to time constraints, this functionality was never implemented; instead, a static colourised filter was made in Blender and imported in the 3D model, to illustrate how it may look like. An example of the filter in a smart phone view can be seen in Figure 5.8. The three colours, green, yellow and red where used as indicators to illustrate the pollution intensity for particulate matter, and reflect the levels given in Table 3.1. A video and demo application was also implemented prior to the user interviews and can be found in Appendix A.2.

```
{
  "type": "FeatureCollection",
  "features": [
    {
      "type": "Feature",
      "properties": {
        "thingName": "00002176",
        "thingType": 761,
        "pm10": 3,
        "pm25": 4,
        "co2ppm": 5038,
        "timestamp": "2020-03-12 16:56:31.521",
        "temperature": 12.88177490234375,
        "altitude": 13.600000381469727,
        "rhum": 21.5087890625
      },
      "geometry": {
        "type": "Point",
        "coordinates": [
          10.393618388318878,
          63.42615433092474
        ]
      }
    },
    ...,
    ]
}
```


Listing 1: Geo-JSON frame of the incoming data from the server

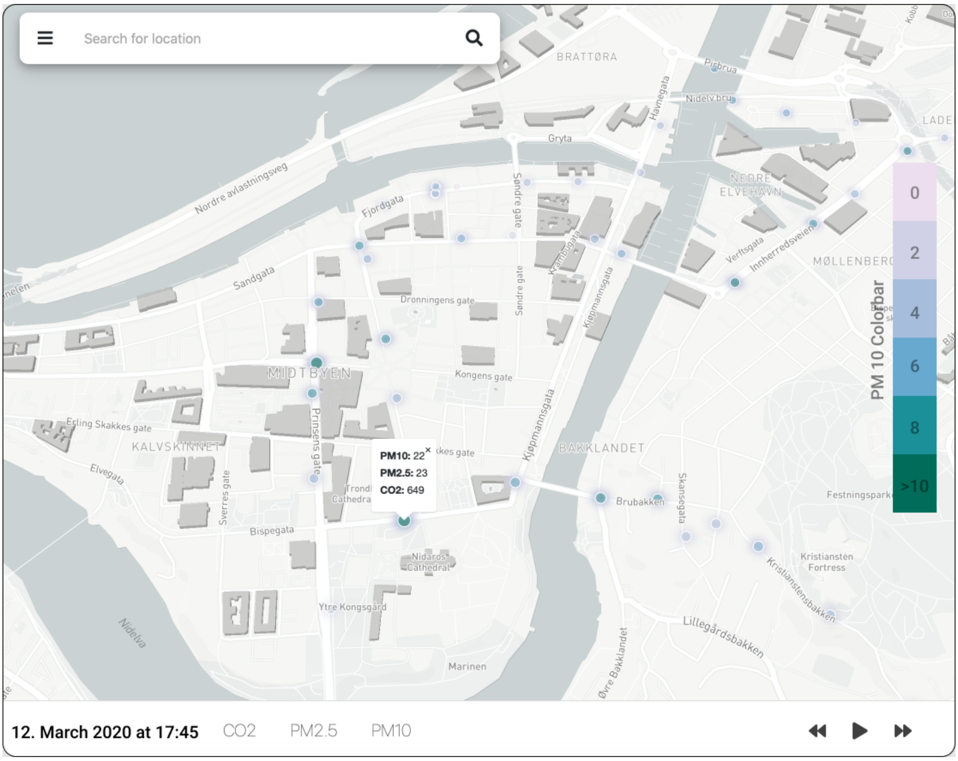


Figure 5.5: Screenshot of the 2D visualisation platform. The walking test performed on the 12th of March can be replayed with the play/pause button so that the user can review the experiment. The marker colour of PM_{10} levels is highlighted in this view.

Figure 5.6: A screenshot from the 3D model of Trondheim. The left view shows the model in grey scale and the right view with colour. A grey scale colour on the background is useful when accentuating pollution particles with color. Water and clouds are added to give the user a realistic feeling.

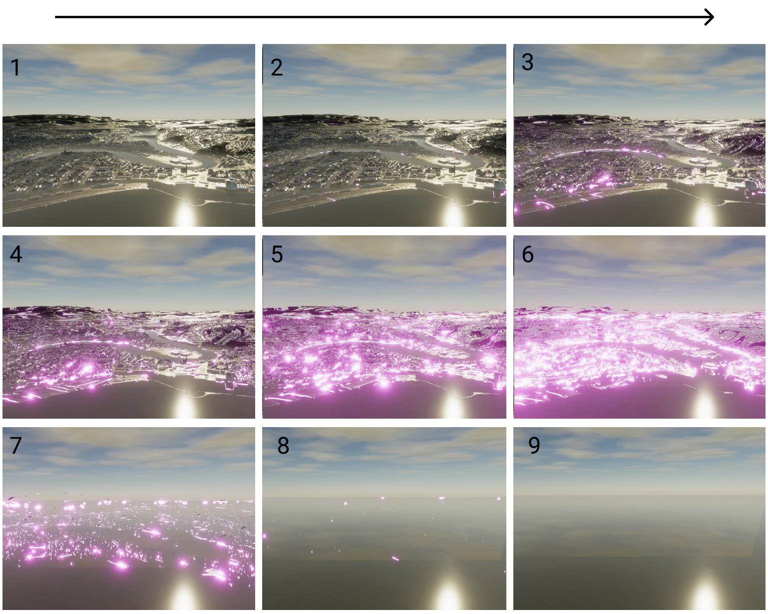


Figure 5.7: An example of how the Particle System toolbox can be used to dissolve elements in the model. Trondheim harbour with Nidelva river can be seen in the background of picture 1 to 9, being gradually dissolved.

(a) None

(b) Red

(c) Red, yellow

(d) Red, yellow and green

Figure 5.8: Illustration how how a 3D-street view of Elgeseter could be presented with color labels red, yellow and green

Chapter 6

Results

This chapter describes the results from sensor experiment performed on the moving bus and summarises the feedback from the user evaluation interviews.

6.1 Visualisation dashboards

In order to make a good decision, the accurate provision of information is necessary. As mentioned in section 3.11 spatio-temporal data analysis could be challenging. A system developer has to consider the data granularity and level of information when creating a visualisation. A high detailed pollution model is constrained by the data provided, and a vast amount of data comes at the cost of processing time. On the other side, a too low information granularity is also not of interest, since this makes a visualisation coarse, causing, for example, a colourized heat map to span over large grid cells. Low granularity could, in turn, make it hard to pinpoint extreme values accurately, or for a stakeholder to limit initiatives such as road cleaning and dust suppression.

A visualisation dashboard implemented in Grafana can be seen in Figure 6.1. Unfortunately, the data provided by our micro-sensors was unstable during the experiment. The issue was mainly due to connectivity problems, with a sudden loss of connection to the cellular tower. Since there was no internal data storage, we suffered from data loss during the downtime.

We discovered that the connectivity problems were due to the cell-tower handover on the device. Since Narrow Band IoT cellular technology focuses on energy efficiency and long range, it is more prevalent in applications with fixed (stationary) devices. With NB-IoT, the device needs to re-establish the cell-network as it moves. In the moving bus experiment, our sensor was therefore not able to connect to the cell tower and transmit the readings, before it had to re-connect to a new cell tower. This issue has been solved in the second generation micro-sensors, by using the LTE-M modem for network connectivity.

A LTE-M cellular alternative has better support for mobility because it handles the handover between cell towers, much like LTE. A LTE-M device would have a smooth cell tower handover and would not drop the connection, while an NB-IoT device joins a single base station and would have to re-establish a new connection after reaching a new cell network [51].

The readings we got from the integrated particle sensor was at a general level very low and stable at all three locations, even in situations where we would expect higher values, such as in the morning and evenings when people commuted to work. A snippet from from a day in May, with $PM_{2.5}$ (red) and PM_{10} (yellow) levels highlighted can be seen in Figure 6.2. The Honywell sensor used in the experiment prototypes are designed for indoor use, and hence have a limited sensitivity to capture the low background concentrations outdoor. Notice how the values of $PM_{2.5}$ and PM_{10} are always shifted with 1 μg/m^3 of each other. The shift was present on all the prototypes during the experiment.

Figure 6.3b show all the received measurements from the moving bus experiment over a period of 6 days from 16-22 of April. Due to the corona pandemic, the number of passengers using the public bus service was lower than normal, and several of the bus lines, including 13 and 14, could to drive with no passengers the entire route. When comparing the spatial distribution in Figure 6.3b with the actual bus route of Line 13 and 14 in Figure 6.3a, we see that many of the data packages are not received. Especially after the red line switch to the blue line the connection drops out for a longer period, due to the cell-tower handover.

Another challenge to consider with NB-IoT is the latency on the uplink connection, where it can take up to 10 seconds to upload the data on the server. This is not appropriate for real-time applications, such as autonomous driving that may require a two-way communication for fast user interaction. However for our bus experiment this is not a problem, since we do not have a real-time critical application, and in most cases aggregate the readings in an historical perspective.

Figure 6.4 shows the 2D application evaluated during the interview session. Participants in all user groups found it clear and useful, especially when a quick overview of the situation is required. A participant from the researcher group commented that it would be helpful with a colour bar in the view to map colours to numbers. Information about a working demo can be found in Appendix A.2. Lastly, during the interview, the user also presented an interactive demo of the 3D heat-map. The demo displayed an example of how a colourized street view model could be presented. Participants from the researcher and policy maker group found this visualisation unclear in a professional setting, and more suitable to target citizens. The results from the user evaluation in Figure 6.5 reflect this viewpoint, where all citizens asked found the 3D visualisation modern and interesting. More information about the working demo can be found in Appendix A.2.

6.2 User feedback evaluation

To evaluate the different visualisation methods, several interviews with people from each user group was conducted. Because of the corona pandemic, all interviews were conducted remotely via Zoom, a video conference platform. A demonstration of the three visualisations line graph, 2D heat-map and 3D heat-map was given to all participants individually during the session. At the end of the interview, a survey was given to get user feedback. The interview guide given can be found in Appendix A.4. Our results from the survey can be seen in Figure 6.5.

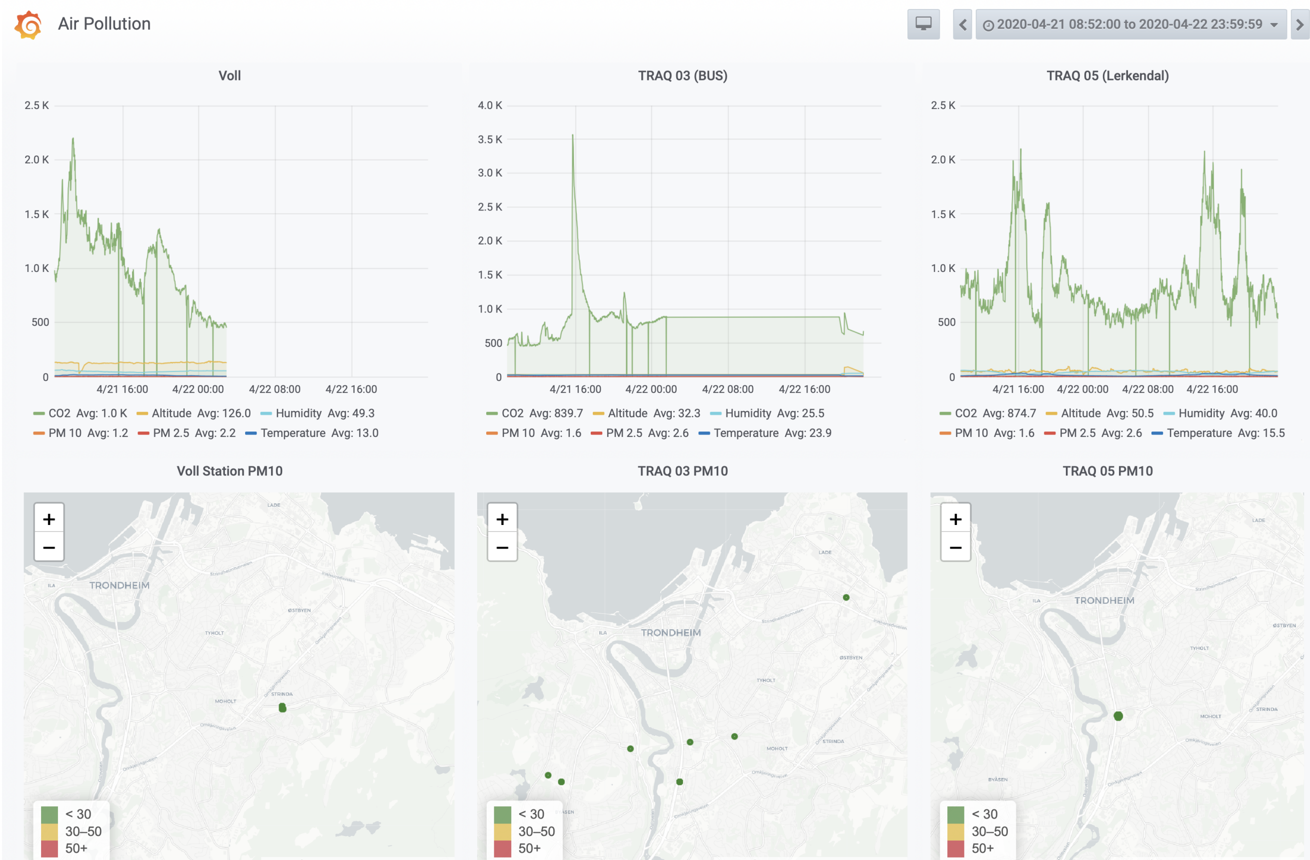


Figure 6.1: A dashboard made with Grafana to visualise the spatial and temporal air quality data. Data is fetched from two stationary low-cost sensors mounted on Voll and Lerkendal, and one moving sensor on a bus.

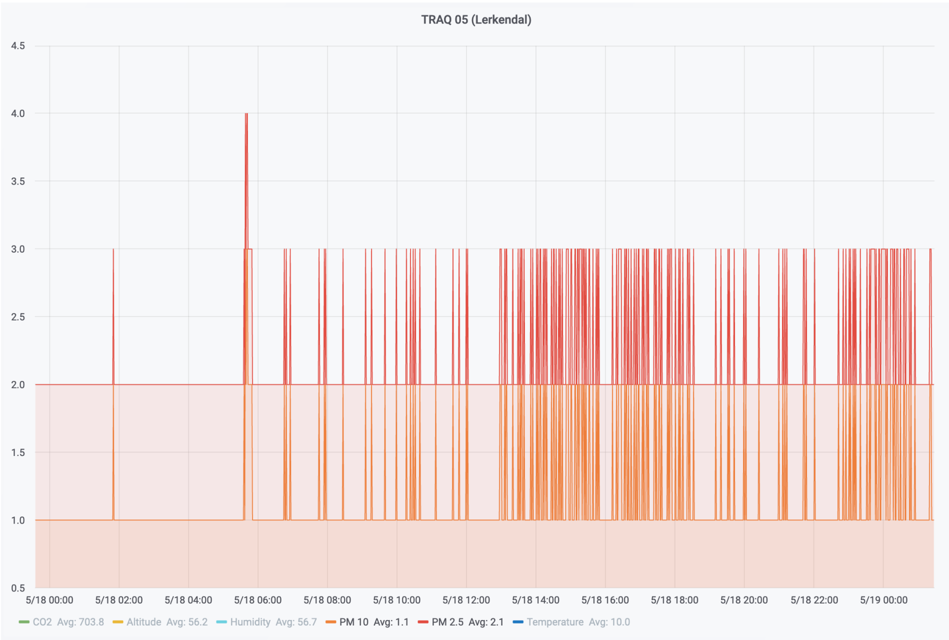
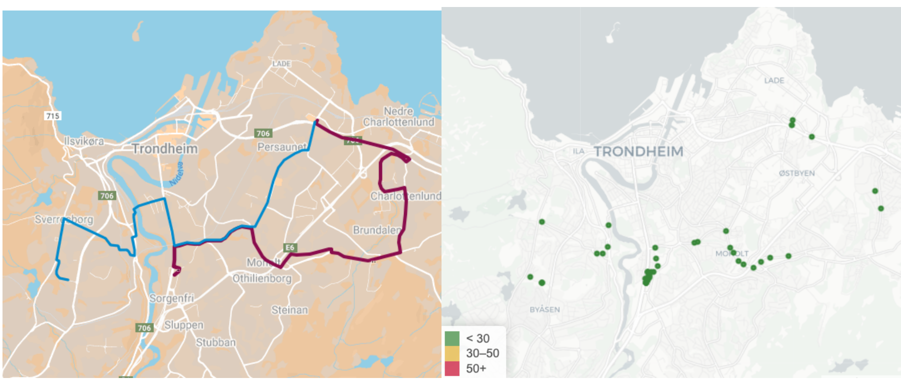


Figure 6.2: $\mathrm{PM}_{2.5}$ and PM_{10} levels are always with shifted with 1 μg/m^3.



(a) Bus line

(b) Sensor measurements

Figure 6.3: The measurement of PM 2.5 captured from the moving bus. Bus line 13 in blue and goes from Strindheim to Havstad. Line 14 in red goes from Lerkendal to Strindheim. The bus line change halfway from 14 to 13.

(a) CO2 **(b)** PM 2.5 **(c)** PM 10

Figure 6.4: Illustration of a 2D heat map view of Trondheim. The colours in green, red and blue illustrates CO2, PM 2.5 and PM 10 respectively. See Appendix A.2 for link to online demo.

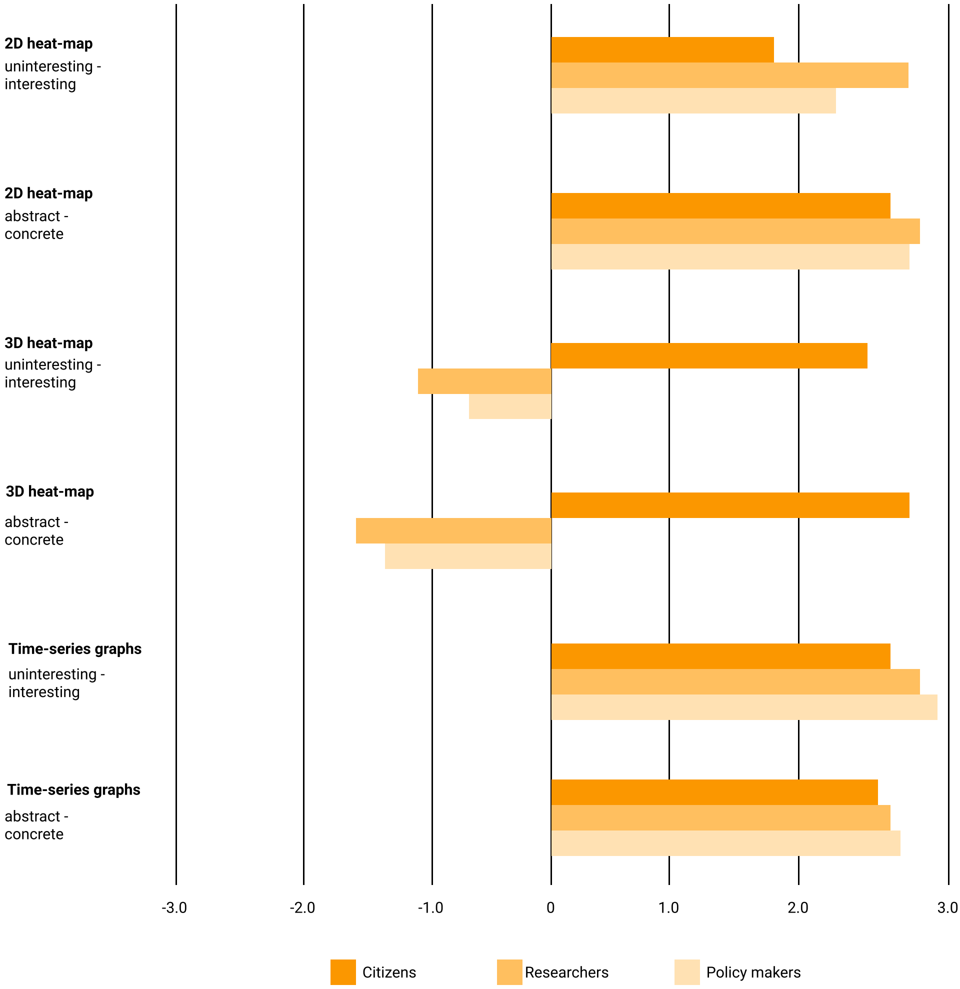


Figure 6.5: Visualisation from the user evaluation results. n = 9 participants (3 participants from each user group); scale ranged from -3.0 to +3.0

Chapter 7

Discussion

The goal of this chapter is to target the research questions defined in Section 1.3 by discussing our results and provide a summary of our findings.

7.1 Stakeholders

This section considers the following research questions

RQ1: Which stakeholders need the information about air quality?
RQ2: What are the decisions for stakeholders to take?

During research on related work and interviews with citizens, policy makers and researchers in Norway, we discovered that the awareness around air pollution and insight in its health effects are low or non-existing. Researchers who directly work with air pollution analysis, or especially sensitive citizens are of course more conscious about the problem, but the general majority was less informed. Our theory why the interest around air pollution is so low in Norway, is because the problem is ”invisible”, and that the air we breath is, compared to other European countries, relatively clean. Everybody should have easy access to information about air quality because it is only with the public perception we are able to create behaviour change. Therefore it is important to continue the work with developing good visualisations that are easy to understand, available and accurate so that trustful decisions can be taken. As for the kids and elderly, whose respiratory functions are diminished, are particularly vulnerable to air pollution. They might however, not be so up-to-date with online information or with the latest mobile applications. It is therefore also important to remember this user group and tailor the information to where they stay or spend their time. Interesting platforms to reach this user group could be through information screens in buses, the local supermarket, or on kinder gardens.

The type of preferred decision to take build upon which user group we asked. In short term a citizen might want to check the air quality upon selecting a route before having a run, and in long term when deciding on a neighbourhood with low levels of air pollution to buy a home. A policy maker needs information about air quality to initiate road cleaning, or to see the effect of measures started. In Norway, the municipalities are liable for control and enforcement of legal requirements regarding local air quality. As described in Section 3.13, road traffic is the dominant local source of air pollution in Trondheim, due to exhaust emission and the widespread use of studded tires. According to the Norwegian Environment Agency, a car with studded tires produces near 100 times more particulate matter than a car with regular tires [1]. A ban or an extra fee of using studded tires is, therefore, an effective incentive a stakeholder could introduce. Reducing the number of vehicles on the road, or motivate citizens to replace the old wood burner stove is two other effective intensives. Researchers want environmental data such as air pollution readings to compare the performance of prediction models against ground truth data and to suggest limit values and target levels for policy makers. They can also use the information to create scientific reports and share it through international agreements and EU directives.

7.2 Provision of data

This section considers the following research questions.

RQ3: What information do stakeholders need in order to make a decisions?
RQ4: What are the benefits and challenges of using micro-sensors for air quality monitoring?

The value of adding mobile air quality monitors on e.g. the bus is that you can obtain air quality concentrations at a high spatial resolution, with a smaller number of sensors over a fixed time frame. A sensor distributed and moving sensor network can capture the high variability that arises in populated urban streets. On the other hand, as seen from our experiment, working with mobile micro air quality sensors comes with difficulty. A mobile sensor capture only a snapshot of air pollution at a given location, resulting in a temporal variability that makes it challenging to identify the air pollution patterns with the measurement alone. In order to develop a detailed map over air quality, large amounts of data, over different traffic and weather conditions are needed. Another challenge with low-cost air quality sensors is reliability and accuracy. An IoT-connected sensor is depended on a stable source of power or a type of energy harvesting technology such as solar panel to charge the battery. This issue was something we discovered during the bus experiment.

A concern we had when mounting the micro sensor on a bus was the fact that the sensor could detect emissions from the vehicle it was deployed. These emissions could vary depending on where the sensor was mounted and can be a significant contributor to the recordings of pollution values. However, since the optical particle sensor used in our experiment detects particles larger than 300 nm[1], and emissions from the busses are particles of sizes around 100 nm [47] we consider these emissions do not have a large impact on our experiment.

[1] https://sensing.honeywell.com/honeywell-sensing-particulate-hpm-series-faq-007607

Having good routines of sensor calibration and comparison to existing reference instruments is needed to provide data integrity.

Because of the challenge with poor quality of our particle readings, as explained in Chapter 6 with Figure 6.2 it would be interesting to redo the bus experiment with the the upgraded second generation prototypes. This prototypes have the OPC-N3 particle sensor from Alphasense, which is designed for outdoor use.

7.3 Visualisation

This section considers the following research questions.

RQ5: What are the possibilities of air quality visualisation?
RQ6: Which visualisation do the stakeholders find useful?

An overview of the results from the user evaluation can be seen in Figure 6.5. We discovered from the interviews that all user groups found the 2D heat-map and time-series graphs useful. Some users in the researcher group pointed out that they do not have any emission estimations for the elevation axis (perpendicular to the ground), and hence it will be difficult to visualise an emission point cloud in 3 dimensions. Another user from the policy maker group outed for the 2D visualisation above the 3D street-view visualisation, due to readability. The user found it easier and quicker to get a situational overview, which is needed when initiating actions such as road cleaning. One requested improvement was to the 2D heat-map visualisation was to add information about model accuracy, such as a confidence ellipse or variable grid cell size on the map. A cleaning vehicle operates in a low-speed range (<5km/h), so significant time-saving factor would be to constrain the cleaning to only high polluted road segments. Users from the citizen group found the 3D simulated street-view visualisation modern and innovative. They suggested that a combination of virtual and mixed reality elements in a smartphone application, similar to the **Clean A/R** prototype, could be an interesting tool to create awareness and behaviour change for the user.

Chapter 8

Conclusion

As a result of our research we found out that the 2D visualisation and historical line graphs were preferred among all user groups; however several individuals in the citizen user group found the 3D simulated street-view visualisation interesting. A combination of an Augmented Reality (AR) application where elements such as smoke or enlarged pollution particles as a filter on the camera lens, is a suggested improvement to the 3D visualisation to create even greater awareness around air pollution. Despite some challenges with battery duration and connectivity during the field experiment, is potential and the possibility of low-cost connected devices endless. We believe that the popularity around air quality will grow in the next years, and we will see a demand for accurate and functional visualisations in the future. Just as we see the growth of crowd sourced weather stations, we will possibly see innovative data-driven IoT-solutions, such as Plume Labs, that in combination with official reference stations will contribute to an even greater spatial coverage. With the power of machine learning and multivariate data analysis, sensors may perform automatic calibration in the presence of a reference station, or fault detection and error correction without human interaction.

8.1 Future work

Changing the user behaviour is challenging, but with digital tools, we can support citizen participation and raise engagement around air quality. Using collaborative formats like a 3D model of Trondheim on a large screen allows the engagement of multiple participants at the same time. Results, for example, from an air pollution simulation, can be presented in a way that is easier to understand than conventional methods. This can, in turn, make participation more attractive, and it can reach out to groups of people that otherwise are not easily included, such as children, elderly and residents with a migration background. The city town hall or the local cinema in Trondheim could be interesting spots where large screens could be facilitated. An example of how air pollution in Elgeseter street could be visualised is illustrated in Figure 8.1.

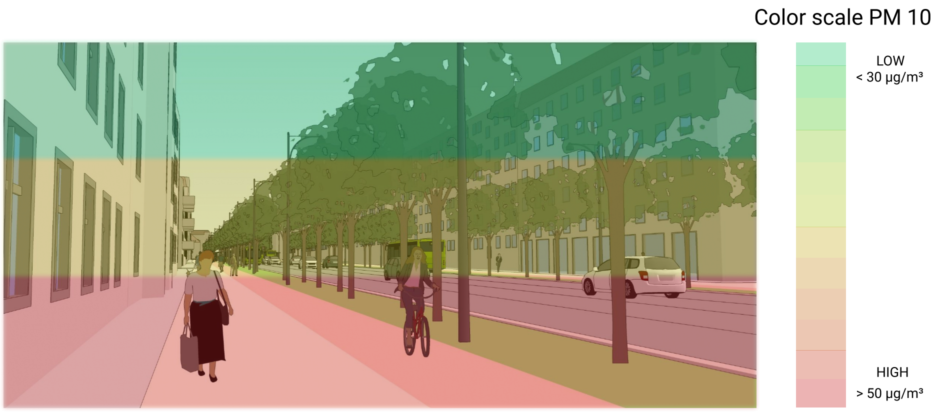


Figure 8.1: Example of a street view visualization with PM 10 colour overlay at Elgeseter street. The pollutant heat map in this figure are not based on true data. Image modified from Miljøpakken [2].

Other ideas discussed during the interviews was to implement solutions in existing platforms and infrastructure. This could be done by using the digital information screens on spots where people commute daily, like the info screens in the bus and public screens on shopping malls that attract people's attention. Utilising popular applications like the Google Maps Travel Planner[1] or Strava[2], could alert people about routes with bad air pollution, and suggest alternative ways to bike or work out. An example of such implementation can be seen in Figure 8.2

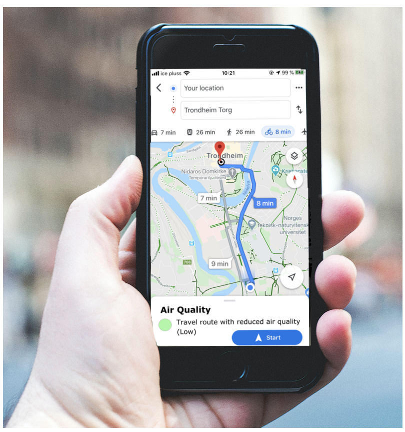


Figure 8.2: Example of implementation in excising services, like the Google Maps Travel Planner

[1]https://www.google.com/maps (site loaded 27.6.2020)
[2]https://www.strava.com/ (site loaded 28.6.2020)

Appendix A

Appendix

A.1 Placement of sensors

Longitude	Latitude	Name
10.3958547	63.4192544	Elgeseter
10.4108893	63.4330346	Bakke Kirke
10.3932933	63.430313	Torvet
10.3717494	63.3576113	Tiller

Table A.1: Table with coordinates and name of NILU stations in Trondheim

Longitude	Latitude	Name
10.3976415	63.4114827	Lerkendal (TRAQ 05)
10.4544539	63.4107538	Voll weather station
-	-	Moving bus (TRAQ 03)

Table A.2: Table with coordinates and name of the Micro-AQ 1st gen stations in Trondheim

Longitude	**Latitude**	**Name**
10.3983664	63.4377464	PwC Building
10.4152164	63.4319669	Bispehaugen skole
10.4135717	63.4234395	Singsaker skole
10.416001	63.4192127	Berg skole
10.3387489	63.3999672	Ugla skole
10.4544514	63.4108607	Voll Station
10.4268978	63.389288	Utleira skole
10.4549294	63.4330697	Strindheim skole
10.5230666	63.4267934	Sjøskogbekken Fus Barnehage
10.426862	63.307451	Tanem skole
10.3428537	63.3508553	Åsheim barneskole
10.3521761	63.3683333	Huseby barneskole
10.3715769	63.4304644	Ila skole
10.4344833	63.4407414	Lilleby skole
10.3785658	63.3565785	Tiller HVS
10.3636985	63.3410573	Sandbakken barnehage
10.1626022	63.3556845	Byneset og Nypantunet HVS
10.4907223	63.4222306	Charlottenlund barnehage
10.4620066	63.4164271	Angelltrøa barnehage
10.393214	63.4303205	Trondheim Torg

Table A.3: Table with coordinates and name of the Micro-AQ 2nd gen stations in Trondheim

A.2 Video and Axure Demo

Figure A.1: The video illustrates how air pollution in Trondheim could be visualised. The 3D model is made in Unity, and Blender is used to add a color overlay. The video is available on YouTube: `https://youtu.be/dd_9yNQeJ3I`

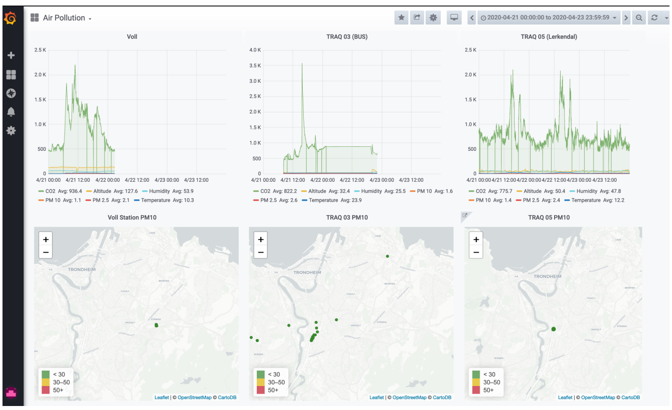


Figure A.2: A video of the Grafana dashboard is available on YouTube here: `https://youtu.be/C-Y1NmDtUpc`

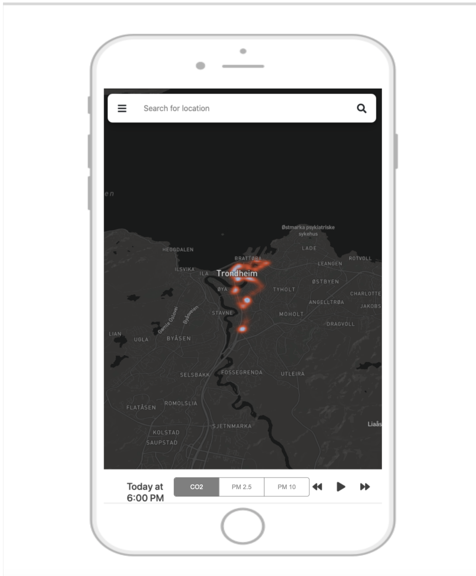


Figure A.3: Mock-up application designed in Axure to visualise how 2D heat-map on the smartphone can be presented. Available here: `https://pgifl2.axshare.com/`

Figure A.4: Mock-up application designed in Axure to visualise how a 3D street view can be presented. Available here: `https://up98io.axshare.com/`

A.3 MQTT subscriber code

```
import sys
import json, requests
from requests.auth import HTTPBasicAuth
from AWSIoTPythonSDK.MQTTLib import AWSIoTMQTTClient
import time
from influxdb import InfluxDBClient

host='localhost'
port=8086
user = 'root'
password = '<db_password>'
dbname = 'airdb'
clientdb = InfluxDBClient(host, port, user, password, dbname)

# Callback on incoming message
def callback(client, userdata, message):
    jsonResponse = json.loads(message.payload)
    state = jsonResponse['state']
    data = state['reported']
    json_body = [
        {
            "measurement": "traq03",
            "tags": {
                "sensor": "traq03",
            },
           "fields": {
                "temperature": float(data['temperature']),
                "latitude": float(data['lat']),
                "longitude": float(data['lng']),
                "altitude": float(data['altitude']),
                "CO2": float(data['co2ppm']),
                "pm10": float(data['pm10']),
                "pm25": float(data['pm25']),
                "humidity": float(data['rhum']),
            }
    }
    ]

    clientdb.write_points(json_body)


client = AWSIoTMQTTClient("<Thing_ID>")
client.configureEndpoint("<Managed-IoT-ats>", 8883)
priv_key = "privkey.pem"
```

```
cert_key = "cert.pem"
root_key = "root.pem"
client.configureCredentials(root_key, priv_key, cert_key)
client.connect()
client.subscribe("$aws/things/<Thing_ID>/shadow/update", 1, callback)

print("Connected")
while True:
        time.sleep(1)
```

A.4 Interview guide

User testing

		Strongly disagree						Strongly agree
		-3	-2	-1	0	1	2	3
S1	I find the 2D heat-map interesting							
S2	I find the 2D heat-map concrete							
S3	I find the 3D heat-map interesting							
S4	I find the 3D heat-map concrete							
S5	I find the time-series visualisation interesting							
S6	I find the time-series visualisation concrete							

Abbreviations

IoT	=	Internet of Things
AQI	=	Air Quality Index
PM	=	Particulate matter
VR	=	Virtual Reality
GPS	=	Global Positioning System
OPS	=	Optical Particle Counter
EMEP	=	European Monitoring and Evaluation Program
NILU	=	Norwegian Institute for Air Research

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