Chapter 2
Sensing the Environment

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2.1 Sensing the Environment: An Overview of the Field

2.1.1 New Approaches in Environmental Monitoring

Systematic environmental monitoring grew out of the concern that people's activities have distinctive impacts on the quality of the environment,[1] with sometimes detrimental effects on the health and wellbeing of all living organisms. This has led to the development of large scale monitoring networks to understand the sources, context and dispersion of various kinds of pollution. Such networks enable improved environmental policy, for instance by identifying appropriate pollution abatement measures and evaluating their effectiveness. The official monitoring networks are highly standardised using high quality precision instruments.

[1] The term *environment* is used here in the narrow sense of the biophysical environment in which organisms live, that affects their health and wellbeing, and that in its turn is affected by their activities. Sensing the environment then means assessing the state of the environment in which organisms live, in domains such as air, water, noise, radiation, ecology or biodiversity.

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Apart from official initiatives, a lot of ad hoc measurement campaigns are carried out by governmental authorities, scientists or non-governmental organizations to understand causes and effects of pollution on a more detailed scale, i.e. to get more spatially detailed information than official monitoring networks provide, to prepare local policy plans or pollution abatement strategies, or to investigate emerging non-regulated pollutants, such as ultrafine particles or endocrine disruptors.

Official monitoring networks typically focus on a limited number of sites at which measurements are carried out with a high level of accuracy (and accordingly a high cost per data). This approach is well suited for monitoring long-term trends in temporally averaged indicators, mainly if the pollutant concentration is only slightly influenced by local pollution sources. In such cases, the accuracy of the equipment allows to discover even the smallest trends. However, this monitoring approach is unable to capture spatial variability and short term fluctuations caused by local sources.

Current innovations in sensing technologies are leading to the development of miniaturised sensors that can be used as stand-alone devices, connected to smartphones or even embedded in smartphones. Provided that such sensors can be produced cheaply enough, they hold the promise of enabling new kinds of intelligent networks that allow monitoring of environmental parameters at significantly higher levels of spatio-temporal detail. Smartphones are attractive consumer devices in this respect because of embedded sensors such as microphones, GPS receivers, optical sensors or accelerometers and their processing and transmission capabilities. Their wide array of local connectivity options (e.g. Wi-Fi, Bluetooth, NFC, USB) makes connecting them to additional external sensors relatively easy. Their touch screens allow developers to design intuitive interfaces for annotation of sensed data, for example to enrich purely quantitative measurement data with qualitative information (e.g. contextual parameters and subjective opinions) to facilitate interpretation. Portability and robustness of these new sensing platforms allow for mobile data collection during walks, bicycle or car rides which could allow for widespread coverage as compared to the stationary monitoring stations. In comparison with conventional, high-accuracy and high-cost environmental monitoring networks, these new sensing networks have the potential to generate environmental data that are more detailed and potentially enriched with contextual information, and to do so at a reasonable price.

These technical developments create opportunities for participatory data collection and monitoring (Burke et al. 2006; SCU–UWE 2013; Stevens 2012). There is a long tradition, especially in the UK, of *citizen science* and participatory data collection in the domains of nature conservation, biodiversity and wildlife research. Citizen scientists have surveyed for and monitored a broad range of taxa, and contributed data on weather and habitats. Roy et al. (2012) give an overview of available technology. Several apps are available that allow to collect geo-tagged photos of spotted flora and fauna, and annotate them. Typically these apps are connected to web-based data sharing platforms where users can upload and visualise data. Examples include iSpot (http://www.ispotnature.org/), iNaturalist (http://www.inaturalist.org/) and eBird (http://ebird.org/). Most of these smartphone apps only make use of geo-tagged and annotated photographs. However, there are some examples which do rely on embedded or add-on sensors. The New Forest Cicada app (http://newforestcicada.info/app) detects the high-frequency call of a cicada species through spectral analysis of audio captured through the phone's microphone (Zilli et al. 2010). The Indicator Bats Program (http://www.ibats.org.uk) uses an ultrasonic detector to capture bat echolocation calls along car transects (Roche et al. 2011).

Initiatives to make radiation detectors available to the public at large received a boost of public interest after the nuclear incident in 2011 at Fukushima, Japan. Ishigaki et al. (2012) describe an ultra-low-cost radiation monitoring system using a PIN photodiode detector (POKEGA) connected to a smartphone via a microphone cable. The smartphone software application handles the complex processing required. Wikisensor (http://wikisensor.com/) and iRad (http://www.iradgeiger.com/) are applications for the iPhone. They are based on the fact that the camera lenses, including CMOS sensors, found on most smartphones, are sensitive to gamma and X waves emitted by radioactive sources.

A lot of attention also goes to noise and air quality sensing, e.g. in urban environments. They are discussed in detail in the following sections.

Obviously, there is more to environmental monitoring than collecting data. Data collection, data processing, presentation and visualisation, and finally interpreting the results and drawing conclusions is often an iterative process in which the collected data are combined with the skills and know-how of researchers to come to valid conclusions. In many cases novel sensors and the collected data do not have the same high quality standards as the analytical equipment used in classical monitoring activities. Data validation and quality control are thus critical issues. Mobile monitoring data are also fundamentally different from stationary monitoring data and require adapted monitoring strategies and data processing methods. Chapter 11 of Part 2 of this book will discuss how these aspects can be embedded in participatory monitoring campaigns.

2.1.2 Requirements for Sensing Devices

In this text we will distinguish between monitors, sensing devices and sensors (Box 2.1). Monitors are high-end instruments for continuous measurements. Sensing devices rely on low-cost sensors to give continuous quantitative readings of a physical property.

There is a strong and intrinsic link between the technological features of sensing devices and the way they can be used in monitoring campaigns. Whether a sensing device is fit for monitoring or not depends on the qualities of the sensing device, on the features that are monitored and on the goals of the monitoring campaign.

Features that are monitored have a temporal and a spatial component. Both can be rather constant or highly variable. Some features, such as air quality or noise, can be highly variable both in space and time.

Spatial and temporal resolution of the measurements has to be in line with the spatio-temporal variability of the features that are monitored. The measurement resolution, the number of point measurements per unit of time or per unit of space, depends both on the temporal resolution of the individual sensor and on the way individual sensors are deployed. Next to the temporal resolution the sensing device is also characterised by its response time. A microphone will respond almost immediately to changes in the sound level. Chemical sensors may respond quite slowly to changes in the air, e.g. because of slow chemical reactions or diffusion processes at the sensor surface.

For *continuous stationary measurements* temporal resolution is constrained by the temporal resolution of the sensor. Sensors with a high response time will lag behind and will not be able to capture short-term changes. The spatial resolution is determined by the density of the measurement grid, i.e. the distance between the individual sensors.

For *continuous mobile measurements* the spatial resolution is determined by the track that is covered, but also by the temporal resolution of the measurements and the speed as the mobile sensor will have travelled a certain distance between two consecutive measurements. A slow response time will lead to a shift in space of the measurements and to an underestimation of the small scale spatial variability. Temporal resolution is determined by the number of repeated measurements, i.e. the number of times the sensing device passes by a certain location.

For *discontinuous monitoring devices* temporal and spatial resolution depend fully on the actions of the operator.

Other important features that determine the way a sensing device can be used are its size and weight, (in)dependence from power supply, data logging and data transfer capabilities, data processing capacities and complexity, i.e. required skill to operate it. The features of a sensor will thus determine the way it can be used.

Box 2.1: Sensors and Monitors

The Oxford English Dictionary defines a sensor as “a device which detects or measures a physical property and records, indicates, or otherwise responds to it”. A monitor is defined as “a device used for observing, checking, or keeping a continuous record of something”. Whereas the term monitor clearly refers to a final consumer product, the word sensor is used both in the meaning of the basic sensing element as in the meaning of the final consumer product.

For the sake of clarity we will use a terminology that takes into account different stages in the level of integration of the sensing elements in final devices:

- A *basic sensor* or just *sensor* is the actual sensing element that transforms an external physical property into an electrical response, together with its packaging and pins to plug it in on an electronic circuit board.

(continued)

Box 2.1 (continued)

- A *sensor device* or *sensing device* is a final consumer product that contains sensors (and often peripheral equipment to make the sensors work in the required circumstances), and gives a quantitative reading of the observed physical property to the user. The term sensor device will be used when we make explicit reference to devices containing basic sensors that can be mass-produced at a relatively low cost (i.e. roughly between a few 100 euros and a few 1000 euros).
- A *monitor* is a final consumer product for high-quality continuous measurements at a high cost (several 1000 s euros)

2.2 Monitoring Ambient Air Quality

2.2.1 Monitoring Requirements

Ambient air pollution is estimated to cause 3.7 million deaths each year (WHO 2014). The air we breathe contains a complex mixture of gases and particles that is highly variable in space and time. Components such as NO_2, SO_2, O_3, CO, particles (PM_{10}, $PM_{2.5}$, ultrafine particles, black carbon or soot), heavy metals and volatile organic compounds (VOCs) have all been associated with detrimental effects on human health and/or ecosystems (WHO Europe 2013). Diseases caused by air pollution include respiratory infections, heart diseases, and lung cancer.

The outdoor air quality is affected by emissions from different sources, such as traffic, industry, agriculture and buildings (i.e. heating). Emitted gases and particles are dispersed by wind and atmospheric turbulence, and can travel over long distances. Pollutants can be transformed in the atmosphere through physical or chemical reactions, and new pollutants can be formed. For some pollutants significant small scale spatial differences in concentration can occur, whereas others are relatively uniform over larger areas. Effects on people's health or on ecosystems are specific for each pollutant. As a result several pollutants have to be monitored over representative time and spatial scales to give a comprehensive overview of the air quality.

In most industrial countries most of the above-mentioned pollutants are regulated, and are monitored in official monitoring stations. These monitoring networks have been part of a successful approach to significantly cut emissions of several air pollutants and improve air quality in recent decades (EEA 2013, U.S. EPA 2012). The monitors that are used, are mostly expensive (typically more than 10,000 € per component). They give well controlled and comparable measurements, but due to their high cost spatial coverage is rather low. Additional monitoring is thus most relevant for components that show strong local variability, and that are most harmful to people's or ecosystems' health. In that sense recent literature clearly shows that intra-urban variability is much higher for ultrafine particles (UFP) and black carbon (BC), than for PM_{10} or $PM_{2.5}$ (e.g. Peters et al. 2013). Although UFP and BC are not regulated, there is increasing evidence of their association with health effects (Janssen et al. 2013; WHO Europe 2013). NO_2 and O_3 are also strongly related to health effects, although health effects associated with NO_2 may be caused partially by other combustion-related pollutants that are emitted together with NO_2 (WHO Europe 2013). Spatial variability is less apparent for O_3. SO_2 and CO are also regulated but in practice levels in ambient air are seldom a cause for concern in most industrialised countries. In industrial areas VOCs can be relevant.

Requirements for indoor air quality monitoring are quite different from outdoor. Outdoor pollutants infiltrate in a building depending on its isolation and ventilation rate. But indoor air quality is also affected by typical indoor sources (i.e. combustion processes, building materials, maintenance products). Typical indoor VOCs, some of which with known health effects, are different from those encountered outdoors (e.g. formaldehyde). Typical concentration levels for VOCs are also in the ppb range. CO can be a direct health threat but only at concentrations way above those usually measured in ambient air. Elevated concentrations of CO_2 (>1000 ppm) can lead to dizziness and reduced ability to concentrate. Elevated CO_2 concentrations can also be used as general indicator for poor ventilation.

For most pollutants the challenge is to quantify $\mu g/m^3$ or parts-per-billion (ppb) levels in a complex mixture of gases and particles with varying temperature and humidity.

2.2.2 Monitoring Gas Concentrations

Instruments for personal or stationary monitoring of CO and O_3 based on low-cost electrochemical and metal-oxide gas sensors are commercially available already for quite some time. Milton and Steed (2007) started using mobile GPS tracked ICOM sensor devices to map CO already in 2005. In an effort to initiate large scale volunteered monitoring programs, several projects, research groups or companies developed portable devices, integrating low-cost gas sensors, GPS and mobile phones (e.g. Dutta et al. 2009; Zappi et al. 2012; Mead et al. 2013). However, some of them focused on the electronics and systems integration, power issues, wireless data transfer, data storage and visualization and paid less attention to the performance and limitations of the used gas or particle sensors.

As a general rule the current generation of commercially available basic metal oxide or electrochemical gas sensors cannot be readily used for ambient air quality monitoring. When using these sensors for outdoor air quality measurements, the main issues are the inherent lack of sensitivity, sensitivity to changes in temperature and humidity, lack of selectivity towards other gases, stability and baseline drift. An important part of the complexity, and associated high cost, of air quality monitors is exactly related to the fact that they have to be highly sensitive, component-specific and independent from external environmental conditions (i.e. weather effects).

2.2.2.1 Low-Cost Gas Sensors

Low-cost basic sensors are commercially available for a broad range of gas species including NO_2, NO, CO and O_3. Prices range from a few to 30 € for metal oxide sensors, and from 50 to 80 € for electrochemical sensors. However, most of these have not been designed to measure ambient air quality. Typical concentration levels for pollutants in ambient air will be much lower than those most commonly experienced in industrial safety monitoring or in emissions testing for which most low-cost gas sensors have traditionally been applied. Sensor specifications and calibration curves provided by the suppliers relate to their typical operating range which is in most cases a factor 100 to 1000 higher than concentrations encountered in ambient environments. Reported sensitivities and detection limits often relate to controlled laboratory conditions for exposure to single gas species.

Parts-per-billion (ppb) level sensitivities have been demonstrated in laboratory conditions for several gas sensors (e.g. Brunet et al. 2008; Afzal et al. 2012; Mead et al. 2013). However, when used in ambient environment intrinsic low detection limits are overshadowed by temperature and humidity effects, and by cross-interference (Afzal et al. 2012; Mead et al. 2013). Response times to gas concentrations in the ppb range can also be significantly longer than those specified for gas concentrations in the ppm range. Finally, repeatability and long term sensor baseline drift are other important issues.

Table 2.1 shows the result of a comparison of sensor measurements with reference monitors from the official Flemish air quality monitoring network between October 2012 and April 2013. For this comparison commercially available gas sensors were collocated right next to the reference monitors' air inlet at a monitoring station at a traffic location. The 30 min averaged sensor data were compared with reference data for CO, NO, NO_2 and O_3. The ozone sensors showed a good correlation (0.83) with the reference ozone measurements. Some CO sensors (Alphasense CO-BF and e2v MiCS-5525 CO) showed moderate (>0.50) correlation with the reference CO measurements. The correlations for the NO_2, NO_x and some

Table 2.1 Cross-correlation between 30-min averaged sensor measurements and reference gas measurements from station 42R801 of the official Flemish air quality monitoring network

	Pollutants			
Sensors	CO	NO	NO_2	O_3
Alphasense CO-BF	0.52 (0.16)	0.41 (0.11)	0.34 (0.11)	−0.32 (0.14)
e2v MiCS-5521 CO	0.31 (0.04)	0.32 (0.04)	0.34 (0.04)	−0.09 (0.11)
e2v MiCS-5525 CO	0.60 (0.02)	0.51 (0.05)	0.56 (0.05)	−0.71 (0.05)
Figaro TGS 2201 CO	0.25 (0.02)	0.32 (0.01)	0.17 (0.00)	−0.48 (0.01)
Figaro TGS 2201 NO_x	−0.78 (0.01)	−0.40 (0.06)	−0.24 (0.05)	0.47 (0.05)
e2v MiCS-2710 NO_2	−0.58 (0.02)	−0.40 (0.06)	−0.31 (0.08)	0.64 (0.07)
e2v MiCS-2610 O_3	−0.67 (0.06)	−0.56 (0.02)	−0.55 (0.05)	0.83 (0.07)
Applied Sensors AS-MLV VOC	0.63 (0.02)	0.43 (0.17)	0.53 (0.15)	−0.44 (0.26)

Averages of four sensors are shown together with the standard deviations between brackets

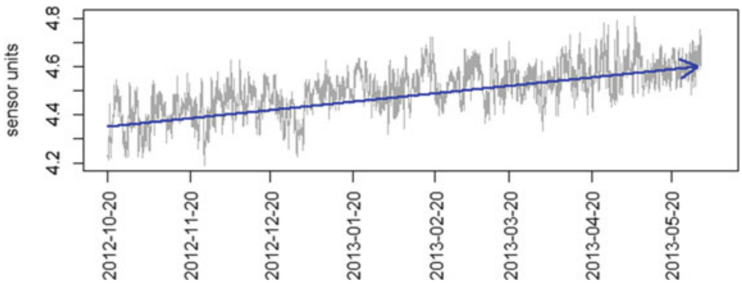

Fig. 2.1 Drift in sensor output signal occurring through time for a metaloxide VOC sensor

of the CO sensors was low. The deviations between sensors of the same type were generally low, indicating similar responses of the different sensors to changing outdoor concentration levels. Cross-sensitivities are observed when sensor data are compared with reference measurements of different pollutants. Some of the observed cross-correlations cannot be explained by known correlation between the ambient concentrations of the pollutants.

Long term sensor drift, i.e. continuous long term changes in the sensor output, was observed for several sensors (Fig. 2.1). These effects are related to sensor ageing, i.e. irreversible changes at the sensing layer.

Recently, Alphasense has a series of electrochemical sensors on offer that specifically target ambient air monitoring (e.g. O_3, NO_2, NO and CO) (Alphasense 2015). Appropriate low noise electronics have to be used to attain the full sensor response. Good design of the sensor, housing and electronics and intelligent data analysis are required, i.e. when measuring O_3 and NO_2. Specifications have to be verified in real ambient conditions.

In the last years a lot of research has been done on the use of nanomaterials and nano-electronics to reach better gas sensing performances and lower power consumption. Nanostructured materials are promising for achieving high sensitivity, but lack of selectivity and stability remain major issues. Most results are acquired in laboratory conditions, and have not yet made their way to field applications. Overviews of the state of the art and future developments are given in Llobet (2013), Afzal et al. (2012) and Basu and Bhattacharyya (2012).

2.2.2.2 Gas Sensing Devices

Different strategies are implemented to improve the sensitivity or selectivity of gas sensors or to compensate for drift. They are based on modulation of temperature regimes, modulation of the flow over the sensor, removal of interfering gases through scrubbers and filters, or compensation for temperature and humidity (Brunet et al. 2008; Bur et al. 2014; Mead et al. 2013). This results in a higher complexity and significantly higher cost of the final device. Prices for commercial devices range from several hundred to several thousand euro for single gas species. The Aeroqual devices are a well described example of how a combination of different techniques leads to the development of an actual device for outdoor air quality monitoring (Williams et al. 2009). Recently also several other devices are commercially available, but only few reports exist in which the use of these devices is compared to measurements from reference devices.

Gerboles and Buzica (2009) evaluated four commercially available ozone measurement devices. Sensitivity to humidity in particular, but also to temperature and in some cases wind speed were apparent during laboratory tests. They compared outdoor measurements with the devices to measurements from a co-located reference monitor. Reasonable measurement results were possible after a field calibration using O_3 reference measurements. Probably the calibration is to a certain extent specific for a site or for different periods over the year. Hasenfratz et al. (2012) made a portable measurement system based on the commercially available OZ-47 O_3 sensor module. They estimated measurement accuracy by comparing mobile sensor readings that were measured in the spatial and temporal vicinity (<400 m and < 10 min) of reference monitoring stations. The errors are on average 2.74 and 4.19 ppb compared to high-quality measurement instruments which they consider sufficient to create accurate air pollution maps considering that the daily ozone concentration typically ranges between 0 and 70 ppb.

However, as mentioned before large scale measurements for O_3 have a limited added value. Measurements of NO and NO_2 would be more interesting, but are even more challenging. Next to baseline drift, cross-sensitivity towards ozone is a major issue for both metal oxide sensors and electrochemical NO_2 sensors (Afzal et al. 2012; Mead et al. 2013). Delgado-Saborit (2012) compared an Aeroqual handheld NO_2 monitor to a reference monitor at 1 h temporal resolution. The concentrations measured by both methods follow a similar trend but correlation is only moderate ($R^2 = 0.63$).

Mead et al. (2013) demonstrated that, when correctly configured, the intrinsic detection limit, sensitivity, noise characteristics and response time of electrochemical sensors are compatible with their use in ambient air quality studies. They used variants of commercially available electrochemical NO, NO_2 and CO sensors (Alphasense, UK) that were optimised for use at ppb level through improved techniques for electrode and sensor manufacture as well as careful design of a low-noise conditioning circuitry. They further present data post-processing procedures to correct for baseline sensitivity to temperature and humidity and to correct for O_3 interference. They compared the corrected sensor data with hourly averages of co-located reference monitors over a 5 day period, and found promising agreement. This is a clear example of an integrated approach in which issues are addressed at the level of the sensor itself, at the level of the sensor electronics and through data post-processing.

Piedrahita et al. (2014) developed parametric regression-based calibration models for commercially available metaloxide sensors, based on both laboratory and field experiments. They included temperature, humidity and a time factor to account for drift. Their experiments revealed that field calibrations using standard reference monitors provide more accurate concentration estimates than laboratory calibrations. However, they didn't test their calibration models on independent data.

2.2.2.3 Sensor Arrays and Multivariate Field Calibration

A way to overcome the gas sensor limitations is the utilization of multivariate information based on information from a set of different gas sensors and/or temperature and humidity sensors together with pattern recognition techniques. This is also known as an electronic nose (e-nose). The sensor array is composed of a selected group of non-specific gas sensors. The different response rates and intensity levels of the sensors in the array will produce characteristic response patterns (i.e. a "finger print") when exposed to volatiles with specific chemical content.

Only few works report the use of e-noses for ambient air quality measurements. De Vito et al. (2009) deployed a low cost multi-sensor device based on seven solid-state sensors at a roadside location 13 months. Models to estimate benzene, CO and NO_2 levels was performed by means of a statistical sensor fusion algorithm, using a neural network (NN) and data from a governmental station as reference. Two weeks of training for their NN was enough to have acceptable results for CO and NO_2 estimation for 6 months. NO_2 levels were quite high with daytime concentrations roughly between 80 and 160 $\mu g/m^3$.

Another example of this approach is the EveryAware SensorBox. A gas sensor array is used to estimate black carbon concentrations in ambient air. Outdoor calibration was carried out for scaling and calibration. A neural network model was parameterized using the calibration data. The model is then used to estimate the black carbon concentration from sensor array measurements. This example is discussed in more depth in Chap. 7 of Part 1.

Sensor arrays seem to have a high potential to counteract selectivity and calibration issues. On the other hand, the sensor array requires a reference device to be deployed for a certain period in its proximity to develop the calibration model. The calibration model can be site and time specific as the specific gas composition will be different for different sites and different seasons. Performance downgrades with time as the gas sensors deteriorate.

2.2.2.4 Mobile Monitoring with Low-Cost Sensors

Most results that were discussed in the previous paragraphs, relate to stationary measurement set-ups. Mobile measurements lead to additional difficulties. As mentioned before field calibration can be site specific, which limits the use of the sensing device to similar locations. The sensor response might be quite different in a busy traffic location and in an urban green. The response time of the sensors is another important constraint. Many gas sensors exhibit response times of several minutes which leads to a spatio-temporal shift in the measurements. In practice a response time of 1 min corresponds to a distance travelled of 80 m for a pedestrian and more than 200 m for a cyclist. In general metaloxide gas sensors have higher response times than electrochemical sensors which makes them less suitable for mobile use.

2.2.3 Monitoring Particle Concentrations

Particulate matter (PM) in ambient air is a heterogeneous mixture of individual particles of different origin, size, shape and composition. Aerodynamic PM diameters are in the 0.01–100 μm range (Fig. 2.2). Coarse particles and PM in the accumulation mode contribute the most to the PM mass in the air. Ultrafine particles (<0.1 μm aerodynamic diameter) have very small mass but are found in very high numbers in air. Primary particles are directly emitted, whereas secondary particles are formed in the atmosphere from precursor compounds. The coarser particle fraction (e.g. with an aerodynamic diameter between 2 and 100 μm) is mainly composed of geological material, pollen and sea salt. Particles smaller than 2 μm include heavy metals, nitrates and sulphates, and carbon particles.

The standard metrics that are actually used in regulation are based on the mass concentration (in μg/m^3) of all particles with an aerodynamic diameter lower than 10 μm (PM_{10}) or 2.5 μm ($PM_{2.5}$). More recently particle number count (PNC, in number per cm^3) is used to quantify the smallest particles (ultrafine particles or UFP) as they hardly contribute to the total mass, but might have important health effects. Elemental carbon (EC) or Black carbon (BC, soot) measurements relate to carbon particles from incomplete combustion emitted as tiny spherules ranging in size between 0.001 and 0.005 μm, and aggregating to particles of 0.1–1 μm.

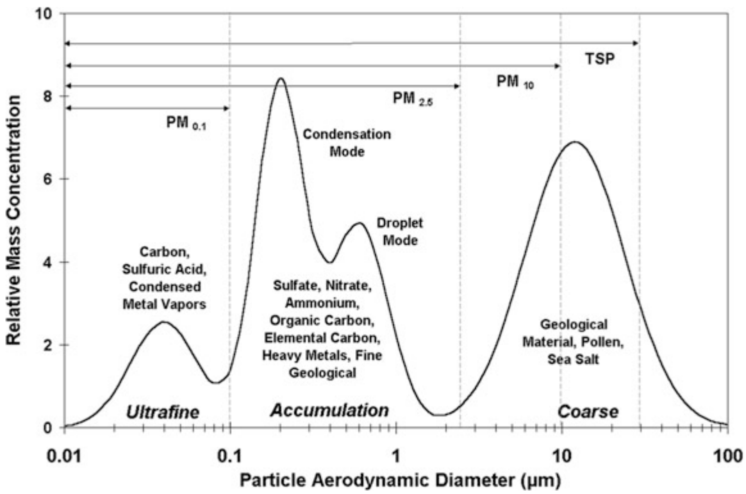

Fig. 2.2 Relative mass concentration in function of the particle aerodynamic diameter

A variety of particle monitors, sensing devices and sensors is available on the market to determine the particle mass concentration in air samples. Different physical principles are used. The most straightforward is the gravimetrical method where particles are actively collected on a filter medium sucking a known volume of air through the filter. Pre- and post-particle collection filter weighing is used to determine the particle mass, and particle mass is divided by the volume of the air sample to determine the average particle mass concentration during the sampling period. Size-selective heads can be used to sample a predefined fraction of particles (e.g. PM_{10} or $PM_{2.5}$). Other particle monitors use Beta attenuation, UV and infrared attenuation, light scattering or oscillating microbalance technology to measure particle concentrations.

Below, we focus on portable particle monitors and particle sensing devices that could potentially be used in ubiquitous or participatory air quality sensing. Participatory monitoring initiatives so far rarely focused on particulate matter. Most existing particle monitors are still quite big, heavy and costly to be used in large scale applications. Further development and miniaturization of particle sensing devices is likely to increase their applicability for participatory sensing.

2.2.3.1 Portable Particle Monitors

Portable hand-held instruments are available for measuring fine and ultrafine particles and black carbon. Examples are the TSI DustTrak, which measures the mass concentration of particles between 1 and 10 µm; the TSI P-trak, which measures the number concentration of particles smaller than 1 µm. The micro-Aeth AE51 measures black carbon mass concentrations. Although these devices are performing relatively well, they have to be compared on a regular basis with standard monitoring devices and sometimes correction factors have to be applied (Dons et al. 2012; Wallace et al. 2011). More recently new devices to measure ultrafine particles have become commercially available (e.g. Mills et al. 2013). With some training, these devices can be used by non-specialist users (Buonocore et al. 2009; Dons et al. 2011). Although primarily intended to monitor personal exposure to particles, they can also be used for general monitoring purposes. But, they are expensive (roughly between 5000 and 10,000 €) which limits their widespread use. In Chap. 10 of Part 2 we will explain in more detail how this kind of devices can be used in participatory monitoring studies.

2.2.3.2 Portable Particle Sensing Devices

Shinyei Technology produces light-weight optical particle counters for different size classes costing about 15 €. The system can report the number of particles or the particle concentration with respect to the selected particle size limits. The AES-1 monitors particulates of 0.5 µm or larger. The AES-4 has particle sizing into four groups: 0.3 and larger, 0.5 and larger, 1.0 and larger, 2.5 (or 5.0 µm) and larger. The PPD42NS measures concentrations of particles larger than 1 μm. Other particle sensors from Shinyei include PPD20V and PPD60V. The Sharp GP2Y1010AU0F is also a compact optical dust sensor of similar cost. It uses a conversion function to convert particle counts to dust mass concentration. The Alphasense OPC-N1 optical particle counter is another small and light weight optical device for measuring particle concentrations of sizes between 0.5 and 15 μm aerodynamic diameter. The Alphasense OPC-N1 optical particle counter is another small and light weight optical device for measuring particle concentrations of sizes between 0.5 and 15 μm aerodynamic diameter. Dylos corporation manufactures compact air quality monitors such as the DC 1100 Air Quality Monitor. The DC 1100 Air Quality Monitor is a laser particle counter to count individual particles of small (>0.5 μm) and larger (>2.5 μm) sizes. The latter two devices are more expensive (200–300 €) but still far below the prices of high range monitors.

Several of these devices have been tested for use in monitoring case studies. Choi et al. (2009) used a Shinyei PPD42NS sensor in combination with several low cost gas sensors as sensor nodes in their APOLLO system. Holstius et al. (2014) made a comparison of the Shinyei PPD42NS sensor with commercially available optical instruments (GRIMM Model 1.108, DustTrak II model 8530) and a reference particle monitor (BAM-1020, MetOne Instruments) at a regulatory monitoring site in Oakland, California. The authors observed negligible associations with ambient humidity and temperature and linear corrections were sufficient to explain 60 % of the variance in 1 h reference $PM_{2.5}$ data and 72 % of the variance in 24 h data. Performance at 1 h integration times was comparable to commercially available optical instruments costing considerably more. Comparison between the hourly $PM_{2.5}$ measurements between Shinyei PPD42NS sensor and Grimm spectrometers Model 1.108 showed *r*-square values of higher than 0.90. The $PM_{2.5}$ mass concentration (24 h average) during the experiments ranged between 2 and 21 μg/m^3. Relative humidity (between 10 and 60 %) and temperature (20–30 °C) were within the operating conditions provided by the manufacturer.

Budde et al. (2013) used Sharp GP2Y1010 sensors in their study on enabling low-cost particulate matter measurement for participatory sensing scenarios. They ran different laboratory and outdoor tests and applied state-of-the-art data models for noise reduction and sensor calibration. When the calibration model was used for consecutive measurement runs, the baseline jumped and the sensors showed drift over time. Baseline drift could be modelled as a function of time. A temperature correction model was introduced in the sensor calibration. On-the-fly calibration with reference measurements is introduced for baseline rescaling of the sensors.

Recently, Steinle et al. (2015) published personal exposure monitoring data of $PM_{2.5}$ in indoor and outdoor microenvironments using the Dylos 1700 device. A validation period of nearly 120 h was used to develop linear functions to convert the particle number counts to mass concentration using simultaneous measurements with a TEOM-FDMS monitor. Afterwards, the Dylos was used for stationary and mobile measurements at different micro-environments. Additional data sources were used for the interpretation. However, the authors correctly state that low-cost air pollution sensing devices do not (yet) obtain the same precision as reference or equivalent methods for measuring PM.

Most case studies using low-cost particle sensing devices are still in an experimental phase in a confined spatial and temporal setting, i.e. under relatively controlled circumstances where a calibration function is developed based on simultaneous measurements with reference instrumentation at the site of final deployment. Long term validity of these calibration functions and their transferability to other areas is largely unknown at this stage.

Next to these experiments with commercially available low-cost particle sensors attempts are also ongoing to further miniaturise particle sensors.

Paprotny et al. (2013) present a micro electro mechanical systems (MEMS) particulate matter (PM) sensor. The sensor measures only $25 \times 21 \times 2$ mm in size. An air-microfluidic circuit separates the particles by size and then transports and deposits the selected particles using thermophoretic precipitation onto the surface of a microfabricated mass-sensitive film bulk acoustic resonator (FBAR). Lab experiments with diesel exhaust and tobacco smoke indicate that it could reach a detection limit below 10 $\mu g/m^3$. The sensitivity can be further increased by increasing the flow through the microfluidic channel. Calibration of the FBAR module is currently FBAR specific. The effects of external environmental factors such as temperature and humidity on the sensitivity of the sensor should also be investigated. The authors envision future devices to contain microfabricated temperature and relative humidity sensors in order to compensate for these effects.

A novel particle sensing system employing zinc oxide based Solidly Mounted Resonator (SMR) devices for the detection of airborne fine particles (i.e. $PM_{2.5}$ and PM_{10}) is currently under development (Thomas et al. 2016). Particles are detected by the frequency shift caused by the mass of particles present on one resonator with the other acting as a reference channel that should compensate frequency shifts that are not related to changes in particle concentration.

2.2.4 Conclusion

Ambient air pollution causes an important health risk, for example in urban environments with a lot of traffic. There is a clear need for additional detailed air quality monitoring for those components that show strong local variability, and that are relevant for people's or ecosystems' health. However, at this point in time there are no readily available solutions for ubiquitous air quality sensing. No low-cost mass produced sensors exist that can directly measure crucial parameters such as PM, BC, NO_2 or O_3 in ambient environments. Their possible availability will be a matter of several years. Some encouraging examples show that the use of low-cost sensors has potential but requires know-how on sensing principles, careful electronics design, laboratory and field testing, and complex data post-processing or field calibration procedures, requiring serious interdisciplinary development efforts. Portable particle monitors and particle sensor devices are available but they are relatively expensive and large which hampers their widespread use. Still there is a clear potential for participatory air quality sensing if monitoring targets are well defined. Possible monitoring schemes will be discussed and illustrated with examples in Part 2.

2.3 Sound Monitoring

2.3.1 Environmental Sound and Its Impact

Noise is a term that people use to refer to unwanted sounds. *Environmental noise* is the term commonly used to refer to noise people are exposed to in their daily lives as a result of various human activities, such as those related to transport, industry and leisure. The labelling of particular sounds as noise is strongly influenced by personal, contextual and cultural factors. Whether the sound is observed at home or in a public space is one of the strongest and most obvious contextual factors.

Since a couple of decades the more general role of *sound* in the public space has become the focus of attention of scientists and practitioners. In this new paradigm, sound is regarded as a resource, and the *soundscape* as an element to be carefully designed and crafted as an integral part of urban design which contributes to the overall well-being of the citizen. This also leads to a strong focus on meaning and appraisal of the sound within its context. Matching monitoring techniques capable of sound identification are needed.

The detrimental effects on health and quality of life induced by long-term exposure to high levels of environmental noise are now widely recognised. The WHO estimates that across the population of western Europe a up to 1.6 million healthy years of life are lost every year due to exposure to environmental noise (WHO Europe 2011). In 2011 the estimated overall societal cost of traffic noise in the EU amounted to € 40 billion a year (European Commission 2011). Annoyance caused by noise can cause chronic stress, anxiety, hypertension and increased risks of cardiovascular diseases. Other adverse health effects include cognitive impairment in children, sleep disturbance, and even tinnitus and hearing loss (WHO Europe 2011). Reported noise annoyance is often used to characterise and estimate the associated health risks. However, even when not consciously perceived, instantaneous reactions of the autonomous nervous system to sound exposure can also contribute to the above-mention hypertension (Lercher 2007). *Noise events*, short-lasting but highly noticeable changes in the environmental sound (e.g. the sound of a train, ambulance or low-flying plane), are known to play an important role in reducing sleep quality.

From a health perspective, the importance of restorative environments has to be acknowledged as well. Green, natural environments and human voices are known to enhance mental restoration (Kaplan and Kaplan 1989; Lam et al. 2010).

2.3.2 Monitoring Requirements

Under the influence of legislation such as the *European Noise Directive* (European Parliament and Council 2002), source-specific *strategic noise maps* have become the conventional method for large-scale assessment of environmental noise. These maps are based on calculations rather than sound level measurements. This method allows to capture the overall spatial distribution of noise, particularly caused by road, rail and air traffic, relatively well. However, when the goal is to capture the smaller spatio-temporal variations in traffic noise, as well as sound resulting from industrial and recreational activities, specific noise events, or sound affecting vulnerable areas (such as schools), it is beneficial, or even required to complement conventional noise maps with more specific and localised monitoring data (Stevens 2012).

In comparison to most other pollutants that can be sensed, sound carries a huge amount of information which can be exploited to identify the nature and the source of the sound.

The primary acoustic parameter which is typically measured is *sound pressure level*, or *sound level* for short, which is a relative measure of the amplitude of sound waves,[2] denoted as L_p expressed in decibels (dB). Sound level is related to *loudness*, which is the subjective measure of how loud particular sounds appear to humans. However, human hearing is not equally sensitive (or responsive) to all frequencies. Therefore, sound level measurements are typically frequency-weighted resulting in an *A-weighted sound* (*pressure*) *level*, expressed in dB(A). To assess environmental noise sound level is typically averaged over set intervals, resulting in the *equivalent continuous sound level*, denoted as L_{eq}, often referred to as *overall* sound level. Equivalent A-weighted levels averaged over 1 h have become very popular basic indicators for the assessment of potential noise exposure effects such as annoyance, hearing damage risk, cardiovascular disease risk and sleep disturbance (WHO Europe 2011). However, most studies proving their predictive power implicitly or explicitly assume that a certain noise source dominates the sound environment, e.g. road traffic sound.

Measuring the *loudness level* (ISO 532:1975)[3] of a complex sound[4] allows to obtain a better estimate of the effects of the environmental sound on humans. It accounts for tonality and clearly noticeable sound peaks, and for the impact of low frequencies. It is therefore worthwhile to include those in more advanced measurements. The meaning of the sounds present in a sound environment is equally important to assess their impact on human health. Measurement systems mimicking

[2]Changes in ambient pressure of a medium (typically air), propagating away for the source of the sound.

[3]Loudness level, denoted as L_N, is a more accurate way to quantify the perceived loudness of sounds, taking into account not only amplitude and frequency but also masking and duration of exposure.

[4]*Complex sounds* are sounds composed of multiple frequencies, as opposed to single-frequency *pure tones*. Virtually all sounds we hear in our daily lives are complex.

human auditory stream segregation are being designed (Boes et al. 2013). Based on a detailed measurement of the sound, these systems try to predict what sounds a human observer is likely to hear (Oldoni et al. 2013).

Measurement strategy and equipment will be different for monitoring the sound in a city to feel its “pulse” or to prepare for more active soundscape design, than for evaluating compliance with noise regulations. For the latter, standardisation of measurement equipment in the form of type classification and strict requirements on measurement location and conditions are included in the national, regional, or supranational regulations. For the former, requirements on measurements strategy and equipment can be more relaxed.

To take into account the local character of noise one can opt for fixed measurement stations that are carefully located to cover all typical situations in the area, e.g. all road types, or one can prefer mobile measurements. The latter allow to quickly obtain a spatial distribution, yet diurnal variations are difficult to grasp. Mobile noise measurements need to be performed with care. In quite environments the noise produced by the observer walking or cycling can disturb the measurements. Sound recognition—or even spectral analysis—can be very helpful to eliminate footsteps or bicycle noise. Citizens could also be asked to move freely and select the sounds and sound levels that they think are relevant. The map constructed in such a way may be less statistically relevant but it could still give useful information for identifying noise problems.

2.3.3 Sound Monitoring Devices

2.3.3.1 Microphone Requirements

The microphone is the most important part of a sound monitoring device. A measurement microphone should have a linear, distortion free response as a function of sound amplitude, a flat spectral response, a low noise floor, limited disturbance of the sound field and limited sensitivity to temperature changes, vibration or electromagnetic radiation. The IEC standards (i.e. IEC 61672-1:2013, 61672-2:2013, 61672-3:2013) specify different categories of sound level meters, based on the accuracy and precision requirements they must meet. The highest-quality category is *class 1* and is aimed strictly at professional usage. Class 1 equipment uses classical measurement microphones of the electret condenser type, which have a low noise floor (20 dB(A) or less) and a flat frequency response over most of the auditory frequency range (20 Hz–20 kHz). They are mounted on a sound level meter that is shaped to avoid reflections at high frequencies. For long term monitoring weather protection is added and the microphone is typically mounted in a free standing position (e.g. on a tripod). Often the monitoring station includes a self-calibration such as charge injection. These high-end monitoring stations are typically too expensive (several thousands of euro) to be used for constructing dense measurement networks or for participatory sensing. Lower quality *class 2* devices are significantly cheaper, but depending on their feature set can still cost several hundreds of euros. When a microphone is used outdoors, wind may significantly disturb the measurement as the turbulence caused by the wind blowing around the microphone produces low frequency signals that are registered as sound. For long-term or permanent monitoring stations protection for wind, rain and condensation is crucial.

2.3.3.2 Cheap Microphones for Use in Sensor Networks and Mobile Monitoring Stations

The quality of microphones designed for consumer electronics is constantly increasing. Spectral response and amplitude linearity is often quite acceptable. The noise floor is however mostly higher than that of the high-end alternatives. Van Renterghem et al. (2011) placed several types of microphones outdoors for an extended period of time to investigate their response under extreme temperatures and their aging in humid environment. The best type of consumer microphone reading deviated less than 2 dB(A) from the reference equipment over a measurement period of 6 months. A limited meteorological dependence was nevertheless observed.

MEMS[5] microphones based on micromachine technology have recently become very popular. The latest digital microphones include analog/digital conversion and even I^2S coding which allow to connect them directly to microprocessor chips. Their noise floor is quite low and impedance issues that might be caused by long wiring are avoided. Nevertheless they sometimes suffer from frost that temporary stalls correct operation.

Sound sensor nodes currently deployed commercially or semi-commercially are either based on class 2 grade microphones or consumer microphones (e.g. Libelium, Sensornet, IDEA-ASAsense). They benefit from a plug and measure design, and start measuring as soon as power is connected. If necessary, they can be managed and updated remotely.

The SmartSantander (www.smartsantander.eu) internet of things (IoT) testbed implements a large number of nodes capable of monitoring noise using Libelium (www.libelium.com) technology. Noise levels are collected together with various other parameters. A-weighting is applied to the WM-61A microphone signal using analogue electronics which makes the computational requirements on the nodes very light. As only overall levels are sampled and transmitted, light IEEE 802.15.4 devices can be used for sensing. The drawback of this technology is that only limited information can be extracted from the sound. Extensions of the SmartSantander sound sensing nodes are being developed.

The IDEA research project (http://www.idea-project.be/) and its derived technology (www.ASAsense.com) focus on maximal information extraction. For this

[5]MicroElectrical-Mechanical System

reason a more powerful single board computer (PCEngine's Alix) is chosen as the backbone of the sensor node. It is combined with a Knowles FG-23329-P07 microphone. 1/3 octave band spectra are sampled 8 times per second since this sampling rate allows to identify most sound events. These big data are stored in central databases for several months. Software agents analyse and interpret the data and store the results in a data-warehouse that can be accessed by users and third party applications. Quantities such as L_{Aeq}, statistical levels, and average spectra that are usually found on sound level meters are available, making the internet of sound observatories resemble a distributed sound level meter. In addition however, psycho-acoustic parameters such as loudness and sharpness as well as a multitude of indicators for spectral content and temporal fluctuation are made available. Finally, and most importantly, artificial neural networks identify the sounds that are most likely candidates to be noticed by a human listener that would be residing at the microphone location. This opens new opportunities for targeted sound management.

The user has to consider whether spectral information (1/3 octave bands) or even more advanced feature extraction and sound recognition are needed, keeping in mind that this might require not only a more expensive sensing device but also more power consumption and higher bandwidth. If 3G/4G has to be used, the price of data transmission may become a significant factor in the deployment of the sensor network.

Mobile measurement devices pose slightly different constraints. For use by pedestrians they should be light and as the battery is a main part of this weight, energy consumption is very important. Data transmission can often be limited to those instances where the device can connect to the internet free of charge.

2.3.4 Participatory Monitoring and Ad-Hoc Measurements Using Smartphone Applications

2.3.4.1 Use of Smartphone Microphones for Environmental Noise Monitoring

In recent years a multitude of free smartphone apps has become available that allow to measure the ambient sound level using the phone's built-in microphone. Examples include NoiseTube (Maisonneuve et al. 2010; Stevens 2012) and WideNoise—both discussed in detail below. This creates opportunities for citizens to use affordable, off-the-shelf mobile phones as tools for ad-hoc sound measurement and participatory noise monitoring campaigns.

As noted before, the accuracy requirements for large-scale noise monitoring or participatory sensing, tend to be lower than those for professional acoustic equipment. For example, in an urban context, it is not necessary to use equipment with a 20 dB noise floor. Many applications (e.g. comparing one street vs. another, or a Monday morning vs. a Saturday afternoon, etc.) typically do not require error margins of <1 dB. Moreover the cheaper equipment also creates a potential for scaling up monitoring efforts. If sufficient amounts of data are available about the same or similar times and places, then the inherent random errors caused by measurement devices of lower quality can be averaged out (Stevens 2012).

Nevertheless minimal quality requirements should of course be kept for any the collected data to be credible. D'Hondt and Stevens used the NoiseTube platform to evaluate the suitability of mobile phones and their microphones as sound level meters and to develop strategies to calibrate such devices to improve accuracy (D'Hondt et al. 2013; Stevens 2012). In the controlled environment of an anechoic chamber they exposed 11 instances of a cheap (∼100 €) feature phone model to pure tone and white noise signals to determine the they accuracy of sound level readings as measured with the NoiseTube application. After a level-dependent calibration[6] the phones performed close to being on par with a Class 2 sound level meter—at least in a laboratory environment and for white noise signals. The tested phones had a noise floor of about 30 dB and spectral responses were found to be sufficiently flat for measuring complex (i.e. multi-spectral) urban sounds at levels above 50 dB . It is plausible that the (hi-end) devices that are on the market now would perform even better, particularly in terms of spectral response (Fig. 2.3).

The influence of wind exposure on sound level measurements can be significant. However, in the case of continuous and mobile monitoring this influence could be eliminated to a large extent by averaging measurements over sufficiently long intervals of time (or space), thanks to the inherent variability of the wind itself, the changing density of urban topography, changes in walking direction, etc. Wind influence, as well as other random errors can also be eliminated by performing repeated measurements across a number of days or weeks (D'Hondt et al. 2013; Stevens 2012).

2.3.4.2 Examples of Smartphone Applications

The *NoiseTube* mobile application (Maisonneuve et al. 2010; Stevens 2012), is available for the Android, iOS and Java ME platforms and is designed with a strong focus on measurement accuracy. It supports A-weighting and can be calibrated for different phone models, or even individual devices. The app is able to automatically download calibration settings for particular phone models via the Internet. The NoiseTube app works as a continuous monitoring device, producing (and storing) geo-tagged series of L_{Aeq} measurements over 1 s intervals. Users can enrich the data by freely adding "tags" to measurements (e.g. to indicate sound sources, subjective impressions, etc.). All data can be transferred to the NoiseTube.net website where it can be shared with other users and noise maps can be generated.

[6]The calibration in NoiseTube is done by applying a level-dependent correction factor to each measurement. Details on the calibration process can be found in (Stevens 2012) and (D'Hondt et al. 2013).

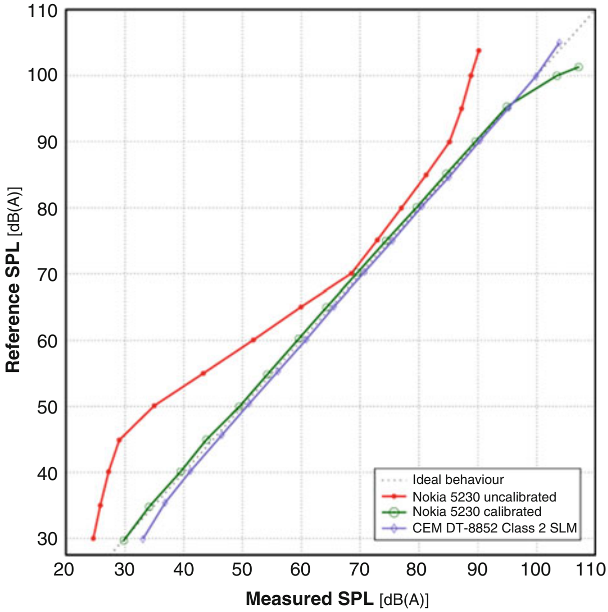

Fig. 2.3 A-weighted sound level measurements of white noise signals by an uncalibrated and a calibrated NoiseTube instance running on a Nokia 5230, and a Class 2 sound level meter [X-axis]; set against the reference levels as measured by a Class 1 acquisition station [Y-axis]. *Source* : D'Hondt et al. (2013), Stevens (2012)

D'Hondt and Stevens set-up two coordinated measuring campaigns with volunteering citizens in Antwerp (D'Hondt et al. 2013; Stevens 2012). Their evaluation covered data quality, usability and organisational aspects. Through comparison of the resulting noise maps with an official, simulation-based map, they found strong indications that support the validity (e.g. capturing expected trends) and added value (e.g. detection of noise that was underestimated by the official map) of the participatory approach, as well as its complementarity with conventional methods for the assessment of urban noise. However, all of this is dependent on rigorous campaign protocols—e.g. using calibrated devices and ensuring spatio-temporal density and overlap.

The *WideNoise* app was originally developed for the iPhone by WideTag, a mobile applications consultancy. Under impulse of the EveryAware project (www.everyaware.eu) WideNoise v3.0 introduced new features, such as the sharing of data through the EveryAware web platform, and was made available on Android as well. This version of WideNoise has been used extensively in participatory campaigns, organised in the context of EveryAware, to monitor noise and assess citizens' opinions about noise exposure (Becker et al. 2013). Widenoise is discussed in more detail in Chap. 7 of Part 1 of this book. Widenoise takes "snapshots": when the user clicks the "measure" button, the app records sound during a short interval of

5, 10 or 15 s, over which the average sound level is then computed. WideNoise does not support A-weighting and measurements are not corrected by means of device or model-specific calibration. Rather than being designed with a focus on measurement accuracy, WideNoise (v3.0) should be seen as a tool created to investigate citizen's awareness, interpretation and learning about environmental noise.

NoiseTube and WideNoise are not the only smartphones apps aimed at facilitating participatory noise mapping initiatives. Several people, often but not exclusively in academia, and sometimes in collaboration with official or non-governmental organisations, have created similar noise monitoring apps and associated web platforms for data sharing or mapping. Examples include *NoiseDroid*, *EEA NoiseWatch*, and *AirCasting*. A comprehensive overview of such initiatives, up to mid-2012, is discussed in (Stevens 2012, Sect. 6.6). At the time NoiseTube was the most complete and likely the most accurate noise monitoring solution for smartphones. It was the first to introduce social tagging, remains one of the few to support A-weighting and the only one that can be calibrated remotely via downloadable settings. However, since then, the Noisemap application, developed by the University of Darmstadt, has pushed the bar by introducing calibration in the frequency domain (NoiseTube only applies calibration in the amplitude domain) and innovative gamification and incentive mechanisms to stimulate user recruitment and retention (Schweizer et al. 2012).

In addition to apps intended for noise monitoring or mapping purposes, the major app stores (e.g. Apple's iTunes Store & Google's Play Store) also contain a wide variety of much simpler apps that claim to act as sound level meters but cannot be considered appropriate tools for monitoring purposes due to highly inaccurate readings, lack of calibration, lack of data logging and sharing features, etc.—some examples are also discussed in (Stevens 2012, Sect. 6.6).

2.3.5 Conclusion

Advances in smart monitoring and internet of things technologies in combination with the availability of cheap and reliable microphones now allow to deploy dense sound monitoring networks at an affordable cost. These networks could equally well be used in participatory sensing with people hosting sound observatories and in smart city applications deployed by authorities. In addition to fixed sensor networks, technology also allows to quickly scan an area using targeted mobile campaigns. Taking into account the richness of the information that could be extracted from the sound signal, it may be worth considering going beyond the sampling of overall A—weighted levels. This allows not only to more accurately mimic the human experience but could eventually also lead to monitoring based control of sound and other emissions.

In addition, the availability of affordable smartphones and sound level measuring and sharing apps creates opportunities for citizens to engage in participatory noise monitoring campaigns.

2.4 Closing Remarks

Current innovations in sensing technologies are leading to the development of miniaturised sensors that could be used as stand-alone devices, connected to smartphones or even embedded in smartphones. Deployment of these sensors in intelligent networks or mobile data collection during walks, bicycle or car rides could allow for widespread coverage as compared to the stationary monitoring stations.

Although there is a clear potential for involving the general public in participatory environmental monitoring, technical complexity depends very much on the parameters that are monitored. The abilities of the sensing devices significantly determine the nature and possible outcomes of such monitoring campaigns. The two parameters that were studied in detail, air quality and sound, both have a strong technological component that will determine the way sensors can be used. Several applications make use of the microphones in smart phones to carry out noise measurements. Several research groups have devoted efforts in developing devices for air quality monitoring in urban environments. However, comparatively little validated measurement results are available.

Low-cost sensors are available, but they have to be optimised for environmental monitoring. The intrinsic data quality that can be achieved, can be improved through changes in the sensor itself. But, to be successful, efforts to use sensors embedded in smartphones or to improve the intrinsic qualities of the sensors themselves have to be combined with development of flexible field calibration strategies and advanced data processing methods. Development efforts partly shift from the intrinsic quality of the measurement itself to data post-processing. In most cases there is need to integrate know-how on sensing technology, electronics, software development and data processing, based on a thorough knowledge of the parameters that are monitored.

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