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Review

The rise of low-cost sensing for managing air pollution in cities

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ABSTRACT

Ever growing populations in cities are associated with a major increase in road vehicles and air pollution. The overall high levels of urban air pollution have been shown to be of a significant risk to city dwellers. However, the impacts of very high but temporally and spatially restricted pollution, and thus exposure, are still poorly understood. Conventional approaches to air quality monitoring are based on networks of static and sparse measurement stations. However, these are prohibitively expensive to capture tempo-spatial heterogeneity and identify pollution hotspots, which is required for the development of robust real-time strategies for exposure control. Current progress in developing low-cost micro-scale sensing technology is radically changing the conventional approach to allow real-time information in a capillary form. But the question remains whether there is value in the less accurate data they generate. This article illustrates the drivers behind current rises in the use of low-cost sensors for air pollution management in cities, while addressing the major challenges for their effective implementation.

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1. Introduction

Road vehicles are one of the major sources of outdoor air pollution in cities (Gurjar et al., 2010; Kumar et al., 2013; Molina et al., 2004). At present, air pollution concentrations are collected by environmental

or government authorities using networks of fixed monitoring stations, equipped with instruments specialised for measuring a number of pollutants, such as carbon monoxide (CO), nitrogen oxides (NO_x), sulphur dioxide (SO_2), ozone (O_3) and particulate matter (PM). Reliability of the measured data is ensured by applying standard procedures for instrument calibration, data collection and post-processing. Typically, regulatory decisions are made based on long duration time-series data that allow for the construction of temporal trends and statistics, while specific conditions related to hotspots are assessed based on real-time data, when available.

In addition, many cities worldwide are adopting mobile laboratories to collect air quality data for specific purposes such as for testing the implementation of a mitigation plan, evaluating a traffic management plan, carrying out feasibility studies, or capturing high spatial and temporal variability in pollutant concentration (e.g. near road-site). A number of publications have reported the use of such mobile laboratories. For instance, Wang et al. (2009) reported the experience of collecting road-site air quality data for the 2008 Olympic Games in Beijing. Padró-Martínez et al. (2012) carried out measurements of air pollutant levels in a near-highway urban environment with a wide range of traffic and meteorological conditions using a mobile monitoring platform, which was equipped with rapid-response instruments. Currently, a few research projects are also exploring the other ways of collecting air quality data. An example of this is the OpenSense project (http://www.opensense.ethz.ch/trac/) dedicated to monitoring air quality in urban areas with mobile wireless sensor nodes to better understand the variation of main air pollutants in cities. Deriving Information on Surface Conditions from Column and Vertically Resolved Observations Relevant to Air Quality (DISCOVER-AQ; http://www.nasa.gov/mission_pages/discover-aq/) is another five-year science project of the National Aeronautics and Space Administration (NASA), USA. This project involves two aircrafts, ground sites and mobile labs to understand air quality in Houston (Texas) in which mobile labs provide critical ground truth to complement information on surface conditions from column and vertically resolved observations relevant to air quality. There is a current trend worldwide to increase the collection of air quality data beyond fixed monitoring stations, although legislation to regulate the usability of these data is not in place yet.

Monitoring of air pollutants is primarily performed using analytical instruments, such as optical and chemical analysers. Gas chromatographs and mass spectrometers can also be used for monitoring, but these are typically used for research purposes due to their complexity and high cost (Clemitshaw, 2004). Usually air pollutant analysers are complicated, bulky and expensive, with each instrument costing anywhere from about £5000 to tens of thousands of pounds, together with a significant amount of resources required to routinely maintain and calibrate them (Chong and Kumar, 2003). Although recent developments in the field have resulted in compact and more mobile instruments, they still have many limitations for widespread use and multi-point sampling (Heard, 2006). Therefore, more solid and compact systems are needed to capture the spatio-temporal variation of air pollution (Peng et al., 2014).

Air quality management is based on an adopted monitoring paradigm (Kim et al., 2012), which is subject to continuous evolution due to technological progress and the development of portable, low-cost (~£100 s) air pollution monitoring devices (i.e. sensors) and wireless communication systems. The adoption of the latter, a key component of low-cost air pollution sensing (DoE, 2010), relative to wired communication systems has been shown to reduce initial investments and annual operating costs by 3- and 5-fold in the US, respectively (DoE, 2010). In Europe, all countries are required to comply with the EU Directives (e.g. the Council Directive 96/62/EC on ambient air quality assessment and management, commonly referred to as the Air Quality Framework Directive). Such directives describe the basic principles for assessing and managing air quality in the Member States, and list the pollutants for which air quality standards and objectives shall be developed and specified in the legislation. These also recommend specific numbers of monitoring stations for individual pollutants, on the basis of the number of inhabitants and geographic partitioning. Demonstration studies have applied mobile sensor networks in some cities, such as Cambridge (UK), Valencia (Spain) and Lagos (Nigeria) (Mead et al., 2013), but their widespread long-term application is yet to find a legislative purpose. Current legislation for criteria pollutants in Europe is set by the European Union (EU) Air Quality Directive 2008/50/EC, which clearly defines the minimum of fixed monitoring stations for each target pollutant. For example, a minimum of one station should be installed every 100,000 km^2, which may exceed the size of some European countries. In this case each country should have at least one station or may set up together one or several common measuring stations by agreement with adjoining Member States.

Given the benefits and concerns related to low-cost sensing, a number of questions remain. In particular: (i) Is there really a need for low-cost air pollution sensing, and if yes, why? (ii) What is the current state-of-the-art of available sensors? (iii) Does this low-cost sensing have the potential to alter the conventional way of monitoring in the future? (iv) Are current sensors sensitive, selective and robust enough for reliable long-term monitoring? (v) What are the major challenges in their production and large-scale deployment in city environments? (vi) Are there any implications of the full life cycle assessment of these sensors and what is the probable cost of dismantling waste?, and (vii) What are the associated gaps on which future research should focus? There are numerous other questions and areas (e.g. energy management) where the use of sensors is popular (Kim et al., 2012), but our focus here remains on the application of low-cost sensing for air pollution management in urban outdoor environments. A comprehensive overview of these questions, highlighting operational challenges and a way forward, is therefore presented.

2. The need

Urban air quality is currently a global concern, which can be attributed to the massive scale of urbanisation and population growth, together with their resultant increases in traffic, industrialisation and energy use (Kumar et al., 2013; Molina et al., 2004). It is understood that technological improvements in low emission motor engines have been offset by an exponential increase in vehicle numbers. Consequently, the release of pollutants into the atmosphere continues to increase (Akimoto, 2003), having adverse impacts on a local, regional and global scale, with significant associated health-effects (Lim et al., 2012). A recent 'Global Burden of Disease' study has provided new evidence of the significant role that air pollution plays globally, placing it among the top ten risks faced by human beings (Lim et al., 2012). Many of the world's cities are unable to comply with the prescribed concentration limits of air pollutants (Kumar et al., 2013; Sharma et al., 2013), and in many cases, reported measurements far exceed them, resulting in millions of premature deaths (Kumar et al., 2014a; Lim et al., 2012; White et al., 2012). At the forefront of pollutants which exceed concentration limits are coarse (PM_{10}) and fine particulate matter ($PM_{2.5}$), and unregulated ultrafine particles (<100 nm) (Kittelson et al., 2004), making this issue even more complex (Heal et al., 2012). For example, a recent World Health Organisation report on ambient air pollution suggests that the annual mean concentration of PM_{10} has increased by more than 5% between 2008 and 2013 in 720 cities across the world (WHO, 2014). A reduction in long-term exposure to PM_{10} by 5 μg per cubic meter in Europe has been reported to "prevent" between 3000 and 8000 early deaths annually (Medina et al., 2004). Similar estimates for $PM_{2.5}$ suggest an average loss of 7–8 months in life expectancy for UK residents and about £20 billion per year in corresponding health costs (Defra, 2008). An equivalent estimate for exposure to ultrafine particles, which have a greater potential for adverse health impacts compared to their larger counterparts (HEI, 2013; WHO, 2013), is currently

unavailable, but will further increase the health and economic burden in the UK and elsewhere (Kumar et al., 2014a).

Air quality varies over a relatively small scale since the resulting pollutant concentration in a specific place depends predominantly on local emission sources and atmospheric flow conditions (Britter and Hanna, 2003). The flow of air masses in urban environments is typically turbulent and difficult to predict without sophisticated numerical modelling tools. Real-time high resolution (<1 m) pollutant concentration maps for large urban areas do not exist at present because they require a large amount of data, computing facilities and input details that are not available for many cities. This complexity makes the assessment of actual human exposure to pollutants challenging (Croxford and Penn, 1998; Vardoukalis et al., 2005). One solution to overcome the lack of small-scale, high-precision measurements of air quality is to adopt low-cost methods for robust environmental surveillance. Although these methods tend to produce lower quality data, they are able to be used in a high number of locations simultaneously, which allows for high-resolution exposure assessment mapping of city environments.

Traditional approaches involve setting up networks of fixed stations for precise measurements of air pollution, which requires significant investment. One such monitoring network is the Automatic Urban and Rural Network (AURN), which consists of about 175 sites across the UK (Defra, 2014). In many cases, these monitoring stations are generally located away from roadsides and major traffic congestion areas, which can create a localised increase in emissions and pollutant concentrations. Spread sparsely around or within a particular city, these stations can provide detailed time-series data (usually with an hourly resolution), but at limited point-based locations. This makes it difficult to compile representative and reliable information for a city or area as a whole, and thereby, to form a more macroscopic view of pollution field trends. Often modelling approaches are used to address this issue, but these might carry inherent aleatoric and epistemic uncertainties due to crude approximations in input conditions (Kumar et al., 2011; Oberkampf et al., 2002). Data from sensor networks could provide more accurate input conditions leading to more robust and reliable conclusions about air quality levels. The deployment of low-cost sensors in significant numbers can also assist in creating emission inventories of pollutants and detecting pollution hotspots, as well as allowing real-time exposure assessment for designing mitigation strategies.

Some research programmes are already using sensor networks to assess their performance for both fixed-site and mobile monitoring (Mead et al., 2013). There are also community-led sensing networks in operation (Air Quality Egg, 2014), allowing the general public to participate in discussions on air quality. Compared to analytical instruments for measuring air pollutants, the sensors which are currently available are several-times less expensive and are easy to deploy, operate and manage. Retrieving data from the sensors is straightforward and their automatic operation allows for wide-spread deployment in the built environment. The use of sensors in this way provides granularity, which better informs the identification of pollution sources and helps support more conclusive studies on the effects of air pollution on socio-ecological justice and human quality of life (Mitchell and Dorling, 2003).

In many cases, data collected from sensors are managed, processed and analysed centrally, sharing the resulting information with all stakeholders, including the general public via mobile phone applications (i.e. apps). This can allow the general public, especially those already at risk, to make informed decisions relating to their health by avoiding areas of high pollution. Although not relying on sensors, such a service is already in place in London through the airText programme (http://www.airtext.info/). There is no reason why similar sensor-based programmes cannot be launched in cities with high pollution levels, such as those in Asia (Kumar et al., 2013; Peng et al., 2014) or elsewhere (Molina et al., 2004).

3. The state-of-the-art

Newly developed sensors are manufactured using micro-fabrication techniques and contain micro-electro-mechanical systems (MEMS) made of microfluidic, optical and nanostructured elements, allowing them to be compact, light-weight and inexpensive (White et al., 2012). These are complemented by sensor circuits that have extremely low-power consumption and energy-efficient communication devices. Advanced computing power for data handling and the wide choice of software packages for data visualisation have made their development and evolution even more exciting (Snyder et al., 2013; White et al., 2012).

The basic components of the sensors are elements that respond to changes in physical or chemical properties, which are converted to electrical signals by the transducers (White et al., 2012). Chemical gas sensors measure the concentration of gaseous species by analysing reactions between the sensing material and target gases, such as O_3, CO, SO_2, carbon dioxide (CO_2), nitrogen dioxide (NO_2) and volatile organic compounds (VOCs). Optical gas sensors measure the adsorption of light by the gaseous species of interest, while light scattering is used for measuring particle number concentrations that can be converted to any mass fraction, such as PM_{10} and $PM_{2.5}$ (White et al., 2012).

Gas sensors work on different operating principles, exhibiting a range of sensitivity, selectivity and response times (Azad et al., 1992; Lee and Lee, 2001). For example, *chemoresistive* gas sensors are widely used for detecting and measuring the concentration of gases in the air. These sensors rely on the release of electrons occupied by adsorbed oxygen on the surface of a semi-conductive nanomaterial (i.e. the sensing element) into their lattice, as a result of the interaction of the target species with pre-adsorbed oxygen. In turn, the electron release induces a change in the density of the conducting electrons in the polycrystalline sensor element and thus, a change in their conductivity (Barsan and Weimar, 2001; Fine et al., 2010). *Capacitance* (or potentiometric) sensors measure the concentration of a number of gases by changes they induce in the dielectric constant of films placed between two electrodes (Pasierb and Rekas, 2009). Changes in the capacitances of the sensing materials in these types of sensors typically fall in the order of a few pF, and are sensitive to operating conditions (e.g. humidity and temperature). *Solid electrolyte* sensors employ cyclic voltammetry, which is widely used in liquid electrochemistry, to determine the concentration of different gaseous chemical species absorbed by a solid electrolyte (Hanrahan et al., 2004). This method probes the oxidation and reduction of the absorbed gas molecules as the potential on the electrode attached to the solid electrolyte is linearly increased. The resulting chemical reaction induces a peak in the current, which is proportional to the concentration of target chemical species. This type of solid electrolyte sensor can be used for the detection of NO_x or SO_x. *Absorption* sensors rely on the fact that gas molecules absorb radiation at specific wavelengths (usually in the infrared region) corresponding to their vibrating energy. For instance, CO_2, CO, and methane (CH_4) have a unique absorbing spectrum at 4.25, 4.7, and 3.3 μm, respectively (Whitenett et al., 2003). Therefore, radiation with a narrow range of wavelengths is often used to enhance the sensitivity of the measurements. This can be achieved by using both filters on the light source and tailored materials as photodetectors.

The development of inexpensive environmental monitoring methods (EuNetAir, 2014; MESSAGE, 2014) has led to the creation of a number of *commercially* available air quality sensors (Alphasense, 2014; Sensaris, 2014) and *prototype* sensor networks (Clarity, 2014; Open Sense, 2014). Such networks are currently operational in the USA (Air Quality Egg, 2014) and UK (SNAQ, 2014). Many of these sensors are calibrated against standard analytical methods and their accuracy can range within ±10% for most air pollutants (Snyder et al., 2013). The calibration procedure of gas sensors is carried out in two steps. The first step (namely the "zero check") determines the response of the sensor when the concentration of the target gas is zero, while the

second step (namely the "span check") determines the response of the sensor when exposed to a gas with a specific concentration of the target gas (TSI, 2014). While the "span check" is relatively easy to perform, the "zero check" is more challenging because there is no established standard for synthetic air or pure N_2 with zero concentrations of impurities. As a result, it is becoming more common to use cleaned ambient air for the "zero check" (Kularatna and Sudantha, 2008). No matter how precisely the calibration of the sensors is performed, they are sensitive to meteorological conditions and need time to acclimatise when the monitoring environment is changed. Some studies have found encouraging results in relation to the performance of CO, NO and NO_2 sensors that can provide parts-per-billion ($\mu g\ m^{-3}$) level mixing ratio sensitivity with low noise and high linearity (Mead et al., 2013). Furthermore, prototype sensors (Bell et al., 2011; Bell and Galatioto, 2013; Envirowatch, 2014) were developed in the MESSAGE (Cohen et al., 2009; North et al., 2009) project, funded jointly by the Engineering and Physical Research Council and the UK Department for Transport, the NUIDAP (Galatioto et al., 2011), for developing an integrated database and assessment platform in response to user needs, as identified through discussions with potential users of pervasive sensor arrays (Bell et al., 2009; Suresh et al., 2009). The first full-scale application of this database and platform was prototyped in Medway (Bell et al., 2011), which confirmed its affordability, as well as its usefulness in understanding the sources of pollution (Galatioto et al., 2014), informing traffic management strategies (Rose et al., 2012) and validating the impact of interventions (Bell et al., 2011). However, their long-term reliability and application for regulatory purposes still remain unclear and need to be assessed scientifically.

Sensor networks require both electrical power and a means of uploading data. Field deployments of sensors for air quality and other measurements (e.g. airflow and water flow in municipal water systems) have relied on a range of technologies. Hardwired power and/or communications backbones used to support generally sparse or relatively expensive sensors are not appropriate for fine-grained deployment of sensors whose purchase price can easily be dwarfed by installation costs that include necessary services. Battery power sufficient for two years of operation of one available sensor pod makes them suitable for extended deployment to detect hot spots, evaluate before-and-after changes in pollutant concentrations associated with urban development and "fence line" detection of pollutants at industrial sites (Air Monitors, 2014). Communication alternatives have included wi-fi links to an available local area network and cellular service, in some cases using General Packet Radio Service (GPRS) that is an integral part of the Global System for Mobile Communications, GSM (Air Monitors, 2014; Mead et al., 2013). Portable versions use blue tooth communications protocol and have batteries comparable to those in mobile phones and intended for daily recharging (Air Monitors, 2014; Sensaris, 2014).

Some real-time sensor-based meteorological networks (Weather Bug, 2014) are already operational in many USA cities, offering online public access through smart phones and personal computers. Likewise, air quality text services which use hybrid modelling (dispersion and forecast) are also currently in operation (e.g. airTEXT in London; http://www.airtext.info/), however the wide-spread deployment of pollution sensors citywide could provide real-time data and reduce the uncertainty associated with modelled forecasting results.

Advances in miniaturised, *wireless-communication* infrastructure (DevLab, 2014; Xively, 2014) mean that these sensors are also capable of reporting high spatial-resolution data in near-real time. Contrary to the conventional, large and costly analytical instruments, such sensor networks are generally compact, remotely-controlled for transmission of collected data, and easy to deploy for unattended monitoring in large numbers (Kumar et al., 2010b). The data acquired from a suite of air quality sensors (e.g. NO_x, SO_2, CO, PM) and accompanying meteorological sensors (e.g. relative humidity, ambient temperature, wind speed and direction) can form the basis for assessing pollution

levels and devising effective control strategies for its reduction (e.g. behavioural changes). However, despite recent progress in the development of low-cost sensors, more effort is required to encourage their wide-spread use in urban environments. Restraining weaknesses that need to be overcome include consistency and durability of the sensing elements, the reliability of the collected data, and the cost of data management and post-processing.

4. Rethinking monitoring via ubiquitous and opportunistic sensing

The idea of ubiquitous sensing (i.e. employing a large number of sensors in a small space) is attracting attention from the air quality management community (Burke et al., 2006; Cuff et al., 2008), particularly given the high availability, low cost and miniaturisation of sensors, which allows them encompass a wider area of the urban environment at a fraction of the cost of conventional instruments (Chong and Kumar, 2003). The development of these sensors has led to a paradigm shift in fine-grained air quality data collection from static and mobile configurations that were not feasible just a few years ago. Moreover, many of these sensors do not require specialised knowledge to be deployed, which encourages public participation in the process (Paulos et al., 2009) and has given birth to the concept of community-based monitoring (Air Quality Egg, 2014), which is driven by local information needs and community values. In fact, low-cost sensing has created the idea of so-called opportunistic sensing, which is using the data collected for one purpose for multiple other purposes as well (Campbell et al., 2008). Anthropocentric opportunistic sensing involves the collection, storage, processing and fusing of large volumes of data related to everyday human activities carried out by the general public in highly dynamic and mobile urban settings (Kapadia et al., 2009). Such datasets are highly useful to environmental health scientists and epidemiologists for gaining unparalleled insight into environmental drivers of individual and community health (White et al., 2012). Likewise, coupling these datasets with clinical information to obtain pathophysiological correlation can improve outcomes of clinical decision-making and care on a more individualised basis (White et al., 2012). Efforts to develop tools that can connect more precise measures of personal exposure to markers of biological response are already under way in the USA (NIEHS, 2014). The use of smartphones as sensing instruments (Lane et al., 2010) provides a further prospect for opportunistic sensing and may assist the transition towards new ways of monitoring the environment.

The distribution of air pollution concentration over large urban areas is determined by rather universal dispersion models and their ability to predict concentrations for emergency situations is limited. Dispersion models are only useful if their quality (fitness-for-purpose) has been quantified, documented and communicated to potential users. The evaluation of emergency-response related models relies on the provision of field datasets of high spatial and temporal resolution. The complexity of a real urban built environment, including the complexity of anthropogenic emission sources and natural variability, makes the continuous evaluation of emergency-response models using up-to-date field datasets even more demanding. Such thorough datasets and evaluations of emergency-response and air-quality models are rather scarce (Neophytou et al., 2011; Shallcross et al., 2009). Therefore, emergency response is an area where sensor networks definitely have a significant role to play in the future.

Furthermore, sensor networks can also activate hazard-warning systems, due to their ability to detect the release of pollutants in the built environment, as well as the accidental release of contaminants from industrial areas. In this respect, sensors for measuring the concentration of hydrogen (H_2) during its production and storage are highly sought after for safety in the emerging H_2 energy sector. This is because H_2 is highly explosive at concentrations above 4% in atmospheric air. Wan et al. (2012) described the application of sensor networks for detecting leaks in natural gas pipelines, in order to overcome the

problems of low-recognition efficiency, high false positive and negative rates and poor localisation accuracy. Therefore, sensor networks might be capable of identifying hazardous leaks in industrial and ambient environments in real-time, in order to offer comprehensive surveillance for the enhanced safety of workers and the general public.

5. The challenges

New technological developments in environmental sensing bring along, as expected, some techno-economic challenges. The most significant of these is the reliability of measured air pollution data, since most gaseous and particulate matter sensors require independent evaluation under a range of ambient environmental conditions (White et al., 2012). Further challenges include improving the sensors' typically short working time (of the order of six months to a few years), as well as their robustness, through rigorous evaluation under a range of diverse environmental conditions. Economic challenges include reducing maintenance (including calibration, battery replacement) and data management/analysis/visualisation costs, which in many cases exceed the cost of the actual sensor system itself. Finally, new challenges lie ahead if the scientific community and decision makers are not prepared to embrace such technology. Awareness, education and technology will have to mature together, in order to bring a paradigm shift in air pollution monitoring.

The main technological challenge regarding the use of sensors for air pollution monitoring is to improve their sensitivity, stability and longevity of operation before replacement. Although most low cost air pollution sensors are sensitive down to a few hundreds of ppb. Considering that most of the important pollutants concentrations are below this limit, there is a pressing need to lower these threshold limits. However, a limitation in improving the sensitivity of the sensors is that many different gases in the ppb range can contribute to the response of the sensors, thereby deteriorating their selectivity. Improving the sensitivity of the sensors without sacrificing selectivity can be overcome by functionalisation, in many cases through controlling the composition (Gaury et al., 2013) and structure (Franke et al., 2006; Julien et al., 2014; Valentini et al., 2003) of the sensing materials at the nanometre scale — a branch of research that drives the material science community at the moment.

Apart from sensitivity and selectivity, other parameters, such as the stability and response time, are also crucial for their selection in specific applications. However, these parameters can be tuned to a certain degree by controlling the composition and structure of the sensing materials (Izu et al., 2003). Despite the simple working principle of these sensors, the gas-sensing mechanisms involve fairly complex reactions. These reactions include oxidation/reduction of the sensing materials, adsorption of oxygen and other chemical species on their surface, and catalytic reactions between the adsorbents. As a result, the performance of these sensors is very sensitive to their operating conditions (e.g. temperature and relative humidity) (Remscrim et al., 2010), and naturally occurring chemical reactions in the urban atmosphere, which vary from daytime to nighttime, as well as pollutant reaction rates may further influence the performance of sensors (Neophytou et al., 2004). Correction factors provided by manufacturers for temperature and relative humidity are adequate at ppm levels (Lane et al., 2010; Mead et al., 2013), but more sophisticated corrections are required for outdoor conditions where sensitivity is required at the ppb level and ambient temperature changes significantly on both diurnal and seasonal timescales (Mead et al., 2013; Shallcross et al., 2009).

Measurements from distributed sensors can be transmitted at almost real-time and stored in databases, and online platforms provide an excellent means for fast and transparent dissemination. Ownership and dissemination of the monitored data provide both challenges and opportunities. This should be addressed effectively and transparently, to benefit the public and help the authorities in air quality management. Data management centres should be established, where data would be stored, validated, processed and modelled into formats which are useful to various stakeholders, such as visual spatio-temporal maps of air pollution, or predictions of concentrations and exposures related to pollution emission patterns and meteorological forecasts. Moving beyond field trials by researchers, it is likely that developers will target municipal agencies as customers, given the need for maintenance and calibration as well as management and analysis of the data. Specific purposes for sensor installation and agency assessment of their accuracy will influence decisions about dissemination of the data. For example, deployment of sensors to isolate hot spots could be followed by the installation of more expensive instrumentation for verification. Portable sensors could be deployed with agency personnel or purchased by individuals interested in their daily pollutant exposure or by contractors making air quality part of the purchase decision of real estate. Here, however, correction of sensor output for variations in temperature and humidity or long-term calibration may at least initially limit the market and inhibit widespread sharing of data. Data from existing sparse networks installed by municipal authorities are increasingly available to the public, revealing data frameworks that could accommodate larger sensor networks in the future (Aquicn, 2014).

6. The future directions

Increasing effort from scientists and instrument manufacturers, as well as improvements in wireless automated systems, have made it possible to reduce the cost of air pollution sensors from thousands to hundreds of pounds or less (Envirowatch, 2014; Air Monitors, 2014). Therefore, at present, the manufacturing (capital) cost of these systems is not a major barrier, however the costs involved in their installation, maintenance and data analysis need to be reduced. In fact, the cost of labour to maintain sensor networks, as well as the post-processing of collected data is likely to exceed the cost of the sensors themselves. The large amount of data expected to be collected by the sensors brings us back to the need for inexpensive analysis, which despite being offered by some high-tech data management and solution companies (e.g. KGS Buildings, 2014), is not yet widely available or affordable. Considering that an enormous amount of data collected by wireless sensor networks has to be routed to a single managing entity, i.e., the network sink, algorithms for data fusion and aggregation (Rajagopalan and Varshney, 2006) are needed to reduce congestion and system overloading (Cao et al., 2006). This is achieved by algorithms processing data collected from the sensors and transmitting only the useful information to the end point.

Current sensors are not capable of measuring ultrafine particles that pose greater risk to human health (HEI, 2013). Although particle sensors for on-board diagnostics (OBD) have already been introduced to the market (Järvinen et al., in press; Stavros et al., 2013), their application for environmental monitoring is currently lagging behind mainly because of their limitation to measure low concentrations. Apart from increasing the sensitivity of these particle sensors, future research is also needed to develop low-cost sensors that can measure the size distribution of particles in the nano-size range. Such data could assist in linking ultrafine particle exposure to exacerbations of chronic obstructive pulmonary diseases, via the simultaneous measurement of physical activity, vital signs and respiratory function. Another related challenge is the sensing of airborne engineered nanomaterials (Kalantzi and Biskos, 2014; Kumar et al., 2010a) which are known to enter urban air through accidental spills or during the use and disposal of nanotechnology products (Kumar et al., 2014b; Lowry et al., 2012; Stone et al., 2010). These nanomaterials are known to deposit in target organs, including the lungs to trigger injurious responses (Nel et al., 2006). Instrumentation to distinguish engineered nanomaterials from background ultrafine particles is currently unavailable and similar low-cost sensors are unlikely to be developed any time soon. However, if they become available, they would be instrumental in measuring the probability density functions of environments that are vital for assessing exposure and

health effects in both indoor industrial environments (where these are produced) and outdoor environments (where generally they can escape during the use of nanotechnology products).

A number of questions still remain unanswered. For example, what would be the future market for such sensors and networks? At least for now, the sensors are not of regulatory quality, nor has their role in informing cause or effect been accepted. Who will pay to instal sensor networks and who will use the data? Will these be regulatory authorities, research funding bodies, commercial entities, or a mix of these or none? Will there be a citizen-owned network? The cost and maintenance of pollution sensor networks are likely to exceed the cost of citizen-owned simple weather stations, so this question still remains unanswered. Electronic waste is already a concern from an environmental and public health perspective (Grant et al., 2013). Ubiquitous sensing has the potential to further add to the e-waste burden after sensors have reached the end of their useable life. Therefore, an analysis of their carbon footprint and potential release of nanomaterials into the environment is necessary, in order to enjoy their benefits without adversely affecting public health, the environment and the earth's ecosystem. It will be challenging for low-cost sensing to match the reliability and robustness of conventional stationary monitors, at least in the near future, but then the question remains — how much of this robustness and accuracy do we really need for what we really want? Can the different desires and needs of different communities converge to some common features? It is perhaps a bit early to accurately answer questions related to the future of air pollution sensing, but the picture will start to become clearer as new information becomes available in the future.

Conflict of interest

The authors declare no competing financial interests.

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