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Cetinkaya, O. orcid.org/0000-0002-7214-6485, Zaghari, B., Bulot, F.M.J. et al. (6 more authors) (2021) Distributed sensing with low-cost mobile sensors towards a sustainable IoT. IEEE Internet of Things Magazine, 4 (3). pp. 96-102. ISSN 2576-3180

https://doi.org/10.1109/IOTM.0101.2100007

Distributed Sensing with Low-cost Mobile Sensors towards a Sustainable IoT

Oktay Cetinkaya, *Member, IEEE*, Bahareh Zaghari, *Member, IEEE*, Florentin M. J. Bulot *Member, IEEE*, Wissam Damaj, Stephen A. Jubb, Sebastian Stein, Alex S. Weddell, *Member, IEEE*, Martin Mayfield, and Steve Beeby *Senior Member, IEEE*

***Abstract*—Cities are monitored by sparsely positioned high-cost reference stations that fail to capture local variations. Although these stations must be ubiquitous to achieve high spatio-temporal resolutions, the required capital expenditure makes that infeasible. Here, low-cost IoT devices come into prominence; however, non-disposable and often non-rechargeable batteries they have pose a huge risk for the environment. The projected numbers of required IoT devices will also yield to heavy network traffic, thereby crippling the RF spectrum. To tackle these problems and ensure a more sustainable IoT, the cities must be monitored with fewer devices extracting highly granular data in a self-sufficient manner. Hence, this paper introduces a network architecture with *energy harvesting* low-cost *mobile* sensors mounted on bikes and unmanned aerial vehicles, underpinned by key enabling technologies. Based on the experience gained through real-world trials, a detailed overview of the technical challenges encountered when using low-cost sensors and the requirements for achieving high spatio-temporal resolutions in the 3D space are highlighted. Finally, to show the capability of the envisioned architecture in distributed sensing, a case study on air quality monitoring investigating the variations in particulate and gaseous pollutant dispersion during the first lockdown of COVID-19 pandemic is presented. The results showed that using mobile sensors is as accurate as using stationary ones with the potential of reducing device numbers, leading to a more sustainable IoT.**

***Index Terms*—Sustainability, IoT, Smart Cities, Low-cost Mobile Sensors, UAVs, Air Quality Monitoring, COVID-19.**

I. INTRODUCTION

The recent progress in the IoT has further enabled Smart Cities by offering connectivity to a vast number of wireless devices. However, the instrumented, interconnected, and intelligent growth of cities is threatened by batteries that the IoT devices rely on, which are capacity-limited and prone to failures driven by external factors. Considering the projected device numbers, replacement and disposal of batteries will be labor-intensive and environmentally unfriendly, making the battery-powered IoT networks impractical and unsustainable.

The second major problem intensified by the proliferation of IoT is spectrum scarcity. There are two possible solutions to prevent wireless infrastructure from collapsing: i) efficient use of the existing spectrum, often referring to cognitive radio technologies [1], which is not (commercially) mature yet; ii) reassignment of the under-utilised/forgotten bands, as has been done recently for 5G, which is not a long-lasting solution since the source is limited, and hence will deplete eventually.

Currently, cities are monitored by sparsely located (stationary), grid-powered, reference stations, which cannot capture local variations since the parameters of interest may differ from street to street in dense urban places. For highly granular data on air quality, weather, road traffic, spectrum usage, and noise levels, monitoring must be ubiquitous. However, being bulky, costly, and stationary hinders such stations' widespread utilisation. Thus, we need low-cost (both capital and operational), low-power (battery-free, self-sufficient), and compact (portable) collaborators providing high spatial resolutions without exacerbating the battery/device/spectrum issue.

Here, low-cost/power *mobile* sensors stand out by achieving distributed sensing with seamless penetration into cities, i.e., reduced device density, so the spectral impact. If the energy required by these sensors is provided via energy harvesting (EH) [2], the environmental impact can also be minimised by removing batteries and their drawbacks, leading to a sustainable IoT. The mobile sensors, however, must interoperate with reference stations for calibration purposes. A small number of low-cost stationary sensors are also required as they can provide long-term observations. Thus, mobile and stationary sensors complement each other for high spatial (via mobile) and temporal (via stationary) mapping of the cities.

The idea of using mobile sensors, however, is not entirely new. Exploiting the public infrastructure, i.e., buses, trams, trains, as mobile sensors has been reported earlier. There are also efforts encouraging individuals (e.g., cyclists, drivers) to join the collaborative efforts on distributed sensing [3]. However, all of these studies focus only on a particular parameter without optimising the system/network for a lower device density in a self-sufficient manner. Hence, this paper introduces a network architecture containing low-cost stationary, mobile, and flying sensors (bikes and unmanned aerial vehicles -UAVs), which extract their energy through EH and adapt emerging enabling technologies. Based on this, a comprehensive analysis of the technical challenges of using low-cost sensors are specified (Sec. II). That is followed by a case study on air quality (Sec. III) that took place in two cities of the UK, Sheffield and Southampton, during the first lockdown of the COVID-19 pandemic, which eventually validated the envisioned architecture. Finally, a discussion on open issues and future research directions are provided (Sec. V).

O. Cetinkaya, S. Jubb, and M. Mayfield are with the Faculty of Engineering, The University of Sheffield, Sheffield S1 3JD, UK. e-mail: {o.cetinkaya, steve.jubb, martin.mayfield}@sheffield.ac.uk.

B. Zaghari is with the School of Aerospace, Transport and Manufacturing, Cranfield University, Cranfield MK43 0AL, UK. e-mail: Bahareh.Zaghari@Cranfield.ac.uk.

F. M. J. Bulot, W. Damaj, A. S. Weddell, S. Stein, and S. Beeby are with the Faculty of Physical Sciences and Engineering, University of Southampton, Southampton SO17 1BJ, UK. e-mail: f.bulot@soton.ac.uk; wissamdamaj98@gmail.com; {ss2, asw, spb}@ecs.soton.ac.uk.

O. Cetinkaya and B. Zaghari equally contributed to this work.

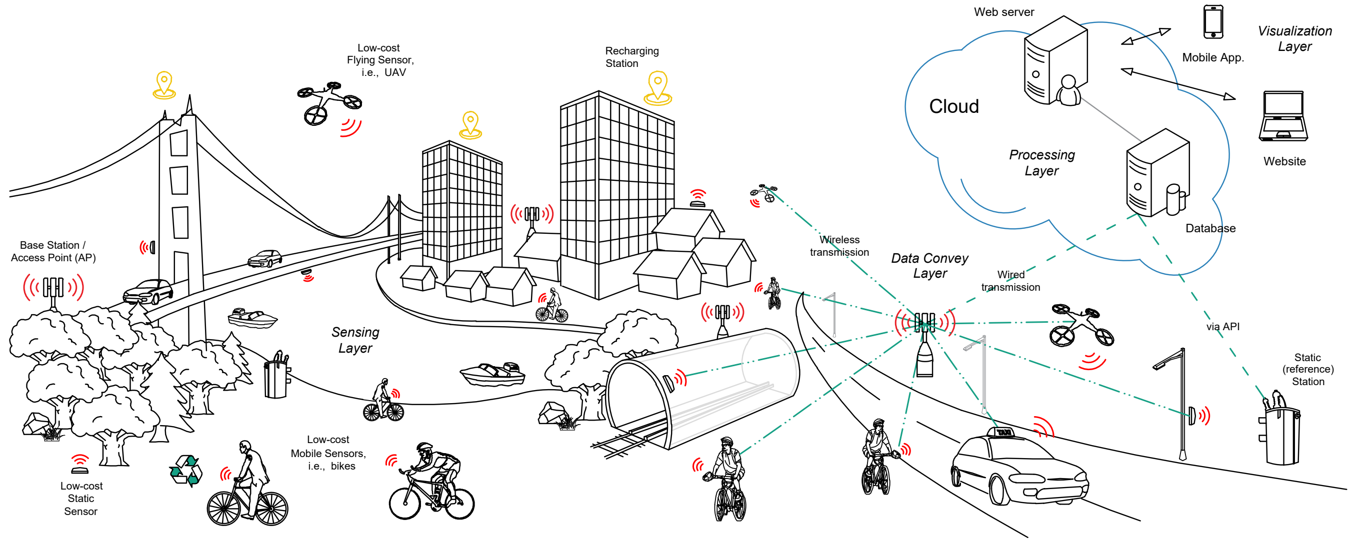


Figure 1: Operation overview of the envisioned network architecture illustrated with its components and layers in a Smart City environment.

II. Operation Overview and Technical Challenges

This section first outlines the conceptual layers of the envisioned network architecture while introducing the technologies to be utilised in its operation. Then, it specifies the unique challenges and the requirements of using low-cost sensors.

A. Network Model and Key Enabling Technologies

As seen in Fig. 1, the network will accommodate stationary (reference and low-cost), mobile (bikes), and flying sensors (UAVs) for high-resolution mapping of the cities in the 3D space. The low-cost stationary sensors will help to increase the temporal resolutions at strategic locations, undertake cross-calibration with mobile sensors and reference stations, and specifically, assess the spatial representativeness of the routes that mobile and flying sensors took, determining whether they are redundant, insufficient, or off-track.

The readily available reference stations are installed by (local) governments, and their numbers usually vary between 3-5 depending on the city size. For mobile and stationary low-cost sensors, a volunteering-based public involvement scheme is required. Here, bikes come to the forefront as the governments are actively promoting cycling to sustain social distancing as a COVID-19 countermeasure.[1] Hence, the number of bikes in cities will proliferate, facilitating the distributed sensing scheme envisioned.

The UAVs, on the other hand, have become cheaper and easier to manage thanks to recent advancements in the field [4], which alleviate their adoption by the system. However, technical challenges like noise, security, and energy usage need to be studied further. The UAVs will be controlled by city officials, who also manage the reference stations, over an IoT-enabled cloud platform. Although the mobile sensors will be dependent on cyclists' routes, their on-demand deployment (for specific needs or re-calibrations) will also be possible.

[1]UK Government's new £2 billion package for cycling and walking. Source: https://www.gov.uk/government/news/2-billion-package-to-create-new-era-for-cycling-and-walking

The low-cost sensors will create their energy budget through EH to achieve self-sufficient, maintenance-free, and environmentally friendly operations. In most urban cities, various EH methods based on ferroelectric, piezoelectric, triboelectric, thermoelectric, electromagnetic, electrostatic, RF, and photovoltaic generators can be used as a source of energy. Among those, triboelectric and thermoelectric have often the highest output power (less than a watt as a peak power). For mobile ones, the most feasible method is to exploit the movement of bikes, thereby converting kinetic energy into electricity. These devices will also be capable of radiative power transfer/reception to enable collaborative energy sharing when they are nearby. For the UAVs, multi-source EH recharging stations, transferring power via inductive coupling, will be situated on top of tall buildings. Alternatively, the UAVs can be self-powered via solar energy.[2]

Data transfer and connectivity in the network will be performed through a centralised approach. In this, the sensors will notify an IP-enabled base station/access point (AP), via a low-power communication protocol (e.g., ZigBee or LoRaWAN), which will then convey the sensory data to the Cloud platform. In addition to readily available ones, the re-charging stations of the UAVs can also be used as APs to allow UAV data to be acquired and transferred during battery replenishment. In some scenarios, the UAVs can act as flying base stations as creating a gateway to the Internet, while also carrying energy from re-charging stations to the low-cost sensors [5].

The AP-conveyed sensory data will be saved into the databases/servers of the Cloud. Here, the centralised computing mechanisms will perform transparent data aggregation, cleaning, and processing, along with Big Data analytics and machine learning-based forecasting. Alternatively, distributed edge computing with federated learning can be adopted in the sensing layer to enable low-cost sensors to make predictions. The *final* data will then be transferred to web servers to be visualised over websites or mobile apps for statistics or government-led generic and/or personalised recommendations.

[2]Solar UAV project. Source: stanforduav.org/projects/solar-uav-project/

Based on the architecture envisioned above, an application-specific guidance for technology selection is provided in Fig. 2. As seen, although the wireless networks cover wide areas with a large number of sensors having low-power consumption and high data rates, they may harm the environment as they are not made of bio-degradable materials. The diagram suggests that a LoRaWAN-enabled network mixing mobile and stationary sensors can reduce the required numbers of devices, so the environmental (and also spectral) impact while maintaining good spatio-temporal coverage. Yet, initially EH, then bio-degradable materials have to be used in sensors/devices.

B. Challenges and requirements of low-cost sensors

- **Optimal sensing location, i.e., *where to sense***: For fine-grained 3D mapping of the parameters of interest, **high spatial and temporal monitoring** is essential. Hence, the sensors require well-planned deployments regarding population density, parameter concentration, and spatial variability of both population and parameter levels. That needs efficient and dynamic **path planning** for bikes and UAVs to avoid overlaps, and hence the waste of scarce resources. An intelligent mechanism deciding on either sweeping the whole area or probing only the specific locations of interest, enabling deep learning-based predictions, is also required.
- **Optimal sensing frequency**: The energy-constrained low-cost sensors cannot make perpetual or periodic observations. Thus, sensory activities often depend on energy availability, i.e., sensing only when possible. This irregular operation reduces the temporal resolution of datasets, requiring careful rethinking while leaving enough room for EH. The added mobility, on the other hand, makes energy reception even less predictable, resulting in varying EH output for each sensor at different times. When a recent reading is reported in its vicinity, a sensor may need to skip sensing in the next power cycle, despite having enough energy, further highlighting its lack of full control on ***when to sense***. Hence, a **location-based, freshness-aware, collaborative sensing mechanism** is crucial to minimise the overall energy cost while optimising the sensing frequency of the network.
- **Optimal reporting frequency, i.e., *when to transmit***: The sensed parameters require **pre-processing** to detect and eliminate noise components, anomalies, and erroneous data. That will improve the monitoring quality and decrease the energy demands for communication and storage. As wireless transmission is the most power-consuming task for low-cost devices, the filtered observations should be further evaluated to decide whether they need to be transmitted. Hence, **event-driven reporting** mechanisms, notifying only when the parameters change, should be adapted for **energy-efficient data reduction**. Nevertheless, the sensors should send occasional beacon signals to inform the analytics platforms in the Cloud that they are still operational, which also indicates no parameter has changed since the last transmission, to preserve data accuracy. Furthermore, depending on the application, some parameters might be more critical than others, requiring **data prioritisation** in queuing, all of which will optimise the reporting frequency of the network.
- **Data heterogeneity**: Sensors with varied capabilities will produce different amounts, frequency, quality, and structure of data, which have to be flattened out before feeding into visualisation, recommendation, and prediction systems. Besides, components of this heterogeneous architecture have to be **interoperable** with each other, and the network should be **scalable** enough to allow flawless addition of new sensors.
- **Re-calibration**: Although all sensors are pre-calibrated by manufacturers, their measurements may diverge from reference stations due to many factors (e.g., sensitivity, vibration). To ensure **high accuracy**, low-cost sensors necessitate **regular re-calibrations**. That is normally done manually, i.e., stopping by a reference station for a while to take concentric measurements. Instead, supervised machine learning techniques (e.g., multiple linear regression and generalised additive modelling) can be employed to compare the results of both devices to calibrate them. The duration of the calibration, however, is still an unsolved issue. In the existing studies, low-cost sensors reside in the proximity of reference stations for a couple of minutes to months, which will not be realistic for volunteering collaborators. Hence, **quicker and more energy-efficient learning techniques** are needed to optimise the calibration duration of bikes, as well as the hovering/pending duration of the UAVs.
- **Low-cost tracking of time and location**: For low-power devices, a real-time clock might not always be practical to employ. That requires **reliable timekeeping** solutions at low-cost, where researchers usually adopt piggybacking-like methods to exploit the ongoing transmissions. Alternatively, capacitor decay or time-intertwined sensing can be used to keep track of time as accurately as possible [6]. On the other hand, dynamic location tracking also requires considerably high power, more than low-cost sensors can afford. Current solutions fulfil the duty-cycled acquisition of location, which

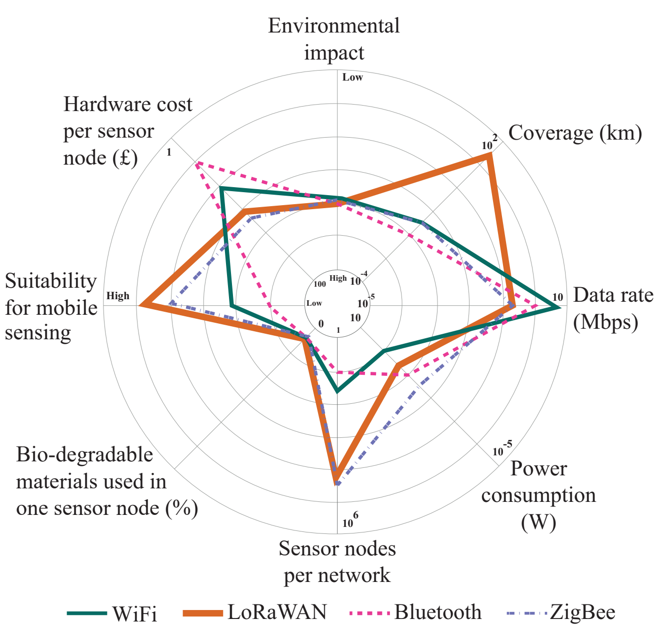


Figure 2: Commercial wireless communication protocols compared for the main criteria of designing a more sustainable IoT.
p.s. qualitative entries are derived from the authors' work in this field.

is useful in obtaining **geo-tagged data at a lower energy cost**. Similarly, accelerometers are employed to use GPS only when moving, hence reducing power consumption. Some studies achieve that even without the accelerometers by using the energy harvested by bikes as an indicator of movement, triggering a location tracker. In such a way, the system acquires the localised data only when a displacement occurs, instead of in a perpetual manner. Hence, the **event-driven tracking of location** can be achieved without any extra hardware cost. For the minimum impact to the low-cost devices, however, AP-led triangularisation or similar 'out-of-budget' solutions should be developed.

- **Preserving safety and privacy**: For areas with low spatial and/or temporal resolutions, on-demand sensing can be fulfilled via bikes or UAVs based on a reward mechanism. However, sending cyclists to the city's underbelly may create risks and unintended consequences, which must be avoided. Additionally, active location tracking in normal operation for high-resolution mapping may raise privacy concerns. Hence, **exhaustive safety measures underpinned by assuring data protection acts** have to be put into practice for individual collaborators.
- **Low-effort maintenance**: The existing networks mainly benefit from WiFi APs/routers for data transfer and connectivity. However, this well-established technology has two major problems: i) *frequent password changes*, occurring due to security purposes or switching between broadband providers due to deals.[3] This non-deterministic behaviour causes frequent service disruptions requiring excessive maintenance, which raise environmental concerns. ii) *limited-range* of WiFi, $\approx 30\,\mathrm{m}$ in urban areas, resulting in wireless devices to demand high numbers of APs to ensure reliable communications. Currently, the number of WiFi APs has exceeded $350\,\mathrm{per\,km}^2$ in cities, with many metropolitan areas reaching over $700\,\mathrm{per\,km}^2$.[4] However, the more APs deployed, the more maintenance needed. Considering also that the RF spectrum is already congested, the wireless infrastructure must be liberated from the burden of WiFi APs. To address these issues, migration to licence-free, low-power, and long-range IoT protocols enabling wide area networks, i.e., LoRaWAN, is suggested. A couple of LoRaWAN gateways can provide full coverage over a medium-size city, as seen in Fig. 3, and hence reduce (multi-hop) routing-based complexity and data traffic in networks. Furthermore, LoRaWAN is immune to changes, i.e., no reconfiguration-driven maintenance costs, as the amendments can be made remotely. Yet, low data rates, retrofit challenges, limited air time, and (new) infrastructure deployment may raise additional issues.
- **Crowdsourcing and incentive engineering for efficient mobile sensing**: Crowdsourcing presents an important opportunity for realising a large-scale distributed sensing system as citizens can contribute readings as they go about their daily lives (e.g., during commuting or while exercising). However, it is necessary to **design the right incentives**, to ensure that large numbers of participants sign up, that they continue to engage with the system over long periods and collect measurements at the right locations and at the right time. A large range of potential incentives exist [7], from financial rewards (e.g., an explicit reward per measurement or the chance to win a prize) to gamification (e.g., awarding scores, badges, or showing contributors on a leaderboard). Besides these extrinsic reward mechanisms, intrinsic motivation can also be a powerful influence on the participants' engagement and can be amplified by providing feedback to them about how their readings provide direct benefit to the overall system. Choosing the right incentive mechanism is often challenging and has to be done carefully since extrinsic and intrinsic motivators often interact with each other in unexpected ways.

(a) (b)

Figure 3: Only one LoRaWAN gateway providing extensive coverage over the cities of (a) Sheffield; and (b) Southampton, UK. Source: https://ttnmapper.org/ (red colour represents the strongest signal).

III. Air Quality Monitoring: A Case Study

Exposure to fine particulate matter (PM) of $2.5\,\mu\mathrm{m}$ or less in diameter ($PM_{2.5}$) causes cardiovascular and respiratory diseases, and cancers, which are associated with millions of deaths globally every year.[5] One of the reasons for these is lack of monitoring, i.e., being unable to take necessary actions, due to the high cost of reference stations. Low-cost sensors have been tested and compared with the reference stations, and a strong correlation has been reported if particular attention is given to calibrating them. The stationary (reference) sites, or commercial high-resolution sensors, are a hundred times more expensive than the equivalent mobile sensor (like the ones presented in this study), making low-cost mobile sensors more suitable in achieving wider coverage. However, the complexity and capacity of the IoT architecture is proportional to the

[3] According to Ofcom's Communications Market Report, 17% of broadband users changed their providers in 2018. Source: https://www.ofcom.org.uk/research-and-data/multi-sector-research/cmr/cmr-2018

[4] Small Cell Forum column. Source: https://www.smallcellforum.org/press-releases/small-cells-outnumber-traditional-mobile-base-stations/

[5] WHO's 2018 Report. Source: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

number of sensors and the required level of reliability, post-processing, data security, and transmission methods [3].

Although collecting pollution data using low-cost sensors has been adopted by several systems, most of them are stationary, and only a few mobile labs/systems are available due to the challenges summarised in Sec. II-B. Capturing pollution data and detecting emission sources, in particular, require localised monitoring, which can be achieved by a combination of stationary and mobile sensors.

Air pollution widely varies based on a range of factors, such as wind conditions, the height of the atmospheric mixing layer, temperature, landscape, and transboundary transport, and is susceptible to interactions between different pollutant types. For PM, the formation of new particles is positively associated with solar radiation intensity, temperature, and atmospheric pressure, and negatively associated with relative humidity [8]. In dense urban areas, the meteorological factors impacting air pollution vary at different scales, from micro- to city-scale [9], supporting the need for a higher number of measurement points to better understand personal exposure. To achieve that and also evaluate the performance of low-cost sensors, $\approx$800 devices of five different brands (AQMesh, Envirowatch E-mote, EarthSense Zephyr, Aeroqual AQY, and EMS AirSonde) were deployed in Sheffield [10], [11]. Some of these sensors were mounted on an electric urban sensing vehicle also carrying a reference station,[6] providing the basis for our distributed (stationary + mobile) sensing concept.

A similar study took place in Southampton, where Fig. 4 shows the daily mean $\mathrm{PM}_{2.5}$ concentrations measured by low-cost PM sensors located in three different places (from March to July 2020). In each location, two Plantower PMS5003 and two Sensirion SPS30 were present. These light-scattering sensors were used within the enclosure described in [12] and were part of the network of low-cost PM sensors described in [13]. The sensors measured data every 1 to $3\,\mathrm{s}$, but for clarity, the data is presented as daily averages. The sites were located in a $750\,\mathrm{m}$ radius from each other, site A at $3\,\mathrm{m}$ high, site B at $1.6\,\mathrm{m}$, and site C at $4\,\mathrm{m}$.

There is a good agreement between the same model sensors with a Pearson coefficient of $r > 0.99$ on each site. While the values reported by the two models of sensors are different, especially during high events of pollution, they also have a good correlation with inter-model r varying between $0.81$and 0.95

There is a little variation between the sites for daily averages likely due to the mixing of PM over the area. The closest reference station, Southampton Centre Background Station, located $\approx 2\,\mathrm{km}$ away from the sites, recorded similar variations for daily $\mathrm{PM}_{2.5}$ concentrations. For a period of time $\leq 1\,\mathrm{h}$, the sensors present more variability. The Pearson coefficients with the reference station, r between 0.94 and 0.96 for daily means and between 0.74 and 0.88 for hourly means, are obtained. The slopes of the linear regression between the sensors and the reference station for hourly data varied importantly between the different months analysed: from 1.56 and 0.81 (Plantower and Sensirion, respectively) in March down to 0.83 and 0.44 respectively in August. These results highlight that while these sensors give a suitable representation of pollution trends, the actual values they report have a large margin of error, typically $> 50\%$. Bulot *et al.* [12] showed that these two models have an intramodel variability of 12 to $31\,\%$, and that they respond differently depending on the composition of the aerosol. Other studies showed that they are susceptible to high relative humidity levels among other factors [3].

To test the suitability of these sensors for mobile sensing on a bike, they were tested under external vibration, which varies vastly from participant to participant and depends on bike type and road conditions. We examined the effects of vibration on these sensors by using a shaker, where the sensors were subjected to base excitation. Since the frequency and amplitude depend on road conditions, a sine wave at frequencies equal to 8-54Hz with maximum 10mm displacement was considered to test both sensors. Higher PM values were recorded, which might be due to more particles moving inside the sensors, where the light scattering method was used for calculating the size of particles. When the results were compared with stationary sensors, Pearson coefficients of $r > 0.92$ and $r > 0.78$ for Sensirion and Plantower were found, respectively. These results were encouraging; hence, the sensors were placed on a bike to be tested on actual roads (blue polygons in Fig. 3 show the routes taken in case studies).

The mobile sensing device shown in Fig. 5(a) contains two $\mathrm{PM}_{2.5}$ sensors (Sensirion SPS30 and Plantower PMS5003), one CO_2 (SCD30 from Sensirion), one combined NO_2 and CO (Grove Multichannel Gas Sensor), one temperature and humidity sensor (Adafruit BME280), one 3-axis MEMS accelerometer (ADXL345 From Sparkfun), one GPS unit (Adafruit Ultimate GPS Breakout), and one LoRa Radio Transceiver (Adafruit RFM95W). Due to the rainy weather and COVID-19 related travelling restrictions, recorded data are sporadic, i.e., once a day between sites A and C (Fig. 5(b)) between 5 PM to 7 PM and from March to July 2020. The cyclist stopped at the location corresponding with each data point for five minutes. In Fig. 4, the average data collected by the sensors (sampling every 8s) on the bike were compared with the stationary sensors (sampling every 1s) only for the duration in which the cyclist was stopped at sites A, B, and C.

Fig. 4 shows the measurements of mobile and stationary sensors. These two cases have the Pearson coefficients of $r > 0.86$, $r > 0.94$, and $r > 0.96$ (for Sensirion) and $r > 0.89$, $r > 0.94$, and $r > 0.94$ (for Plantower) respectively at sites A, B, and C, showing good agreement. Differences exist due to bike movement and the different altitudes of the sensors from the bike. Given the good agreement between mobile and stationary sensors, we conclude that mobile sensors can complement the stationary ones in covering larger areas, thereby achieving high spatial resolutions at a lower cost and environmental impact.

Fig. 4 also shows that the $\mathrm{PM}_{2.5}$ levels during April and early June (during the height of the first COVID-19 lockdown in Southampton), are considerably greater than other months examined in this study. These results are consistent with the values measured in Sheffield,[7] which are against the

[6]The MOBIUS Project. Source: https://urbanflows.ac.uk/mobius/

[7]The Urban Flows Observatory, Sheffield. Source: https://sheffield-portal.urbanflows.ac.uk/uflobin/ufportal/

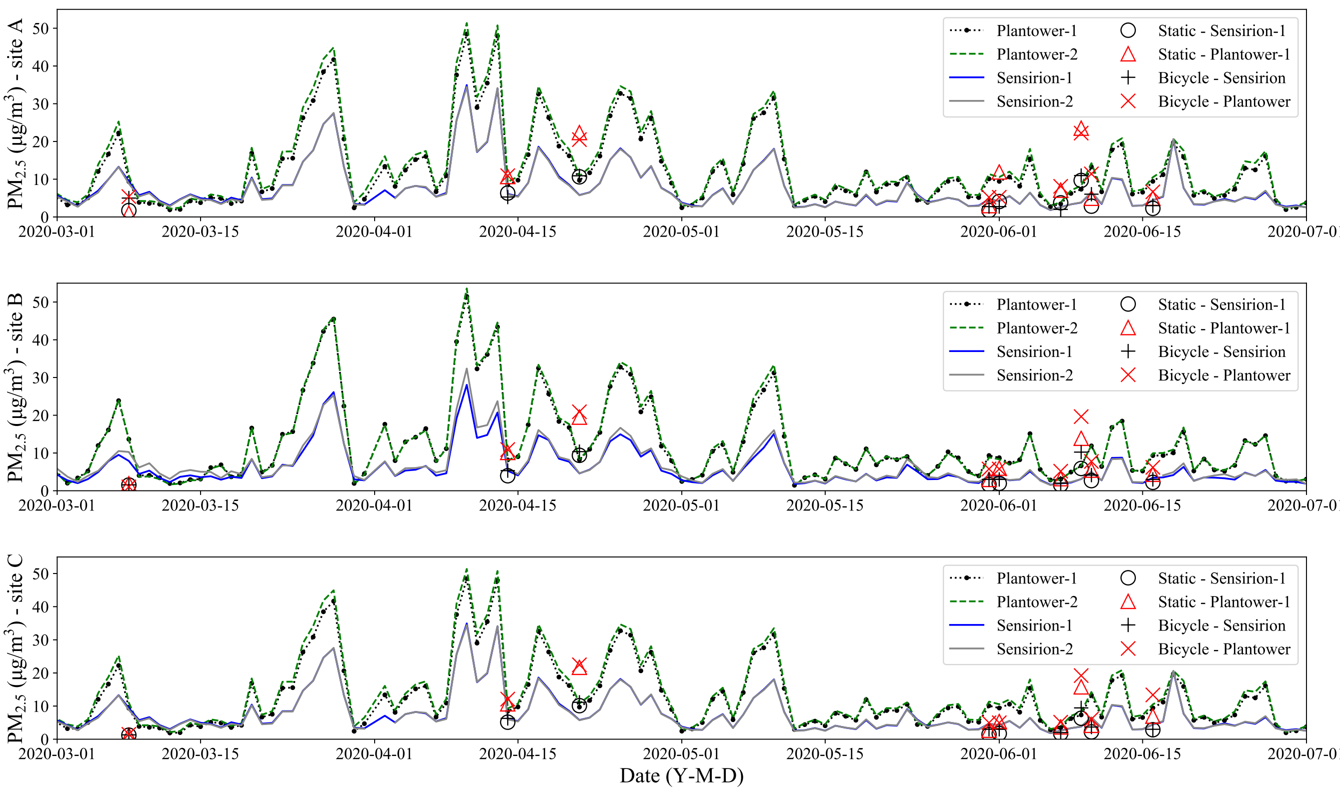
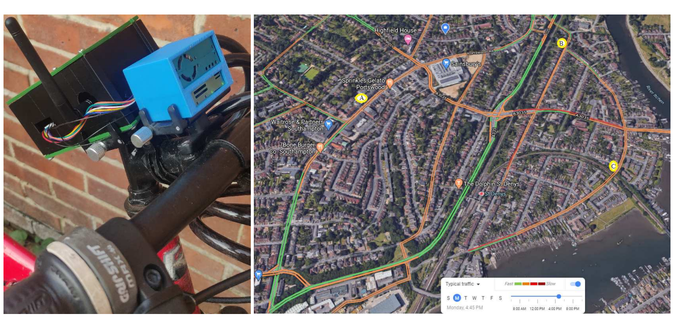


Figure 4: Daily mean $\mathrm{PM}_{2.5}$ concentrations were measured by three stationary low-cost PM monitoring stations (sites A to C). The lines represent the daily means collected by the stationary sensors. The points indicate the averages collected by the sensors on the bike and the stationary sensors at peak time based on local traffic report (between 5 to 7 PM) for days that cyclist stopped at each station for five minutes.

expectations that anticipated a decrease due to COVID-19 restrictions. The high $\mathrm{PM}_{2.5}$ levels, compared to the averages for the same periods in the previous years, can be attributed to a range of factors including abnormal weather conditions, the provenance of the masses of air from the continent, an increase of residential biomass burning, i.e., wood-burning and garden waste, and farming activities that have proceeded as normal during the lockdown [14].



(a) (b)

Figure 5: (a) The low-cost mobile sensor attached on the bike's handlebar; (b) stationary and mobile sensors at sites A, B, and C in Portswood area, Southampton, UK. The cycling route was between A to C from the main roads. The colours on the right-hand side show the typical traffic in the area where sensors are located and the cyclist roams. Red is heavy, orange is medium, and green is no traffic.

IV. Future Research Directions

The low-cost sensors used in the case study highlight some of the challenges: (1) the accuracy of these sensors is questionable and not straightforward to quantify, but expected to improve as the technology they employ progresses; (2) their susceptibility to other environmental factors supports the need for a platform enabling to sense a range of parameters; and (3) the adoption of calibration methods insuring a known level of accuracy, the frequency of re-calibration, and the need for cost-efficient calibration strategies. The good agreement between the stationary and mobile sensors observed here is encouraging as mobile sensors could be calibrated when they pass in the neighbourhood of reference stations, and then be used to calibrate low-cost stationary sensors, which could then also be used to calibrate the mobile ones passing nearby in an automated way. However, to achieve a sustainable mobile sensing paradigm, a low-power sensing design should adopt a competent energy harvester. It can also benefit from wireless power transfer on-board with the mobile network [15].

The network of sensors proposed here can then produce data that can be integrated with reference grade data, satellite imagery, and models to increase the understanding of the spatio-temporal characteristics of pollution over wide areas. The sensors can be used to determine the impact of intervention measure on pollution in the case of road closures, and facilitation of active transport or clean air zones.

Novel algorithms that can effectively relocate the sensors in the desired locations are essential to increase the sensing coverage. Furthermore, game-theoretic strategies deriving optimal mobility for low-cost sensors and targets from their own perspectives or decentralised and localised algorithms, namely Optimal Geographical Density Control (OGDC), must be implemented to determine the optimum number of sensors. The nonlinear relationships between the coverage, connectivity, and energy consumption derive these optimisation problems, which need further investigation for energy-efficient task scheduling and hence the best performance achievable.

AI-assisted, context-aware source recognition and elimination must be performed with the support of photos, videos, and sound recordings. Furthermore, neural engines should be trained using historical data for the spatial fitting of the areas with no or insufficient measurements. That is also useful for making short-term predictions in consideration of external factors, such as the variations in temperature and relative humidity, as well as vibrations. Mobile sensors should provide information on noise pollution generated by the UAVs and allow them to choose the appropriate routes. The collected/generated information should be made accessible to both authorities and citizens to allow them assessing the potential risks and future hazards, contributing to mitigation efforts, and promoting healthier living environments.

Following Sec. II and the outcomes of the case study, our next efforts will focus on injecting low-cost flying sensors into the envisioned network architecture to achieve high spatio-temporal mapping in the 3D space. We will also make all sensors EH-capable, deploy the UAV re-charging stations, adopt the afore-mentioned technologies, and thus evolve this concept to a complete solution for cities. To also show that the envisioned architecture is applicable to any domain, we will perform distributed spectrum sensing, instead of air quality monitoring, to assess how the ever-changing urban landscape affects the performance of wireless networks in cities.

V. Conclusions

This paper introduces a network architecture comprising low-cost sensors to achieve high spatio-temporal monitoring in cities with a lowered impact on spectrum and environment. The technical challenges encountered when using low-cost stationary, mobile, and flying sensors are specified. The enabling technologies to be adopted and the specific requirements to be met are also highlighted. To show the potential advantages of using such architecture, a case study on air quality monitoring with stationary (reference, low-cost) and mobile sensors (mounted on bikes) is presented. The data collected during the case study showed that low-cost stationary sensors could provide similar results with reference stations, promoting the idea of low-cost sensing. That was followed by the assessment of low-cost *mobile* sensors, which illustrated conforming trends with its stationary counterparts, paving the way for high spatio-temporal resolutions with lower spectral and environmental impact by reducing the required device numbers, thereby leading to a more sustainable IoT.

Acknowledgment

The funding used for this work is as follows: UK Engineering and Physical Sciences Research Council (EPSRC) under grants EP/P010164/1, EP/P016782/1, and EP/V022067/1; Research England's Connecting Capability Fund (CCF) award CCF18-7157 - Promoting the Internet of Things via Collaboration between HEIs and Industry (Pitch-In); Next Generation of Unmanned Systems Centre for Doctoral Training supported by the Natural Environmental Research Council under grant NE/N012070/1; the Leverhulme Trust through the Southampton Marine and Maritime Institute. We would also like to thank the Breathing Spaces project from The Southampton Collective CIC for facilitating the data collection.

The data used in this study can be found at https://doi.org/10.5281/zenodo.5218522.

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Oktay Cetinkaya received his B.Eng. degrees (Hons.) with a double major in Electrical Engineering & Electronics and Communication Engineering from Yildiz Technical University, Istanbul, Turkey, in 2013 and 2014, respectively, and his Ph.D. degree in Electrical and Electronics Engineering from Koc University, Istanbul, Turkey in 2018. He worked as a Research Fellow with the University of Southampton after his Ph.D. Since April 2020, he has been a Research Associate with the University of Sheffield. His research focuses on energy harvesting and wireless-powered communications for the Internet of Things, on which he has published around 25 scientific articles in top-tier journals and conference proceedings.

Bahareh Zaghari received an M.Sc degree (Hons) in Electromechanical Engineering in 2012 from the University of Southampton, UK. She received her Ph.D. in Dynamic analysis of a nonlinear parametrically excited system using electromagnets from Institute of Sound and Vibration (ISVR) at the University of Southampton in 2017. She was a Research Fellow at the school of Electronics and Computer Science at the University of Southampton, UK and she was working on the design of smart systems, such as the next generation of jet engines and smart cities. She is currently a Lecturer in Propulsion integration with Canfield University, UK.

Florentin Bulot is finalising his PhD at the University of Southampton. His multidisciplinary PhD is on the characterisation of low-cost sensors for air pollution and how networks of these sensors can improve our understanding of air pollution. He obtained the EPSRC Doctoral Prize to advance further the results of his PhD. Previously, Florentin worked as a consultant in an environmental engineering consulting firm with varied institutions including the World Bank and the UNDP and graduated in 2013 as a generalist engineer from the French engineering school Ecole Centrale Paris. His research interests revolve around the improvement of the quality of life and well-being in urban areas, with a recent interest for nature based solutions. Florentin holds a Permaculture Design Certificate.

Wissam Damaj a BEng (Hons.) Electronic Engineering graduate from the University of Southampton, UK. Graduated in 2020, he has been interested in creating embedded electronic circuits to aid the research involved in wireless communications as well as projects involving next-gen smart cities. He has also been involved with research involving supporting next-gen wireless communications using deep learning classification, and have lately taken on a career in RTL design and verification.

Steve Jubb received a BEng (Hons) from Queen Mary College in Electrical & Electronic Engineering (Telecommunications), and then had a career with British Telecom, Concert and AT&T, spanning the UK and US, supporting large, global companies, addressing their telecommunications needs. Later, he earned an MSc (Eng) in Environmental and Energy Engineering at the University of Sheffield (TUoS) and went on to contribute to research into Smart Grids, Smart Buildings, the Internet of Things and Urban Observatories. He is currently the Chief Technical Officer, Urban Flows Observatory at TUoS, and his current interests include radio spectrum occupancy in urban environments.

Sebastian Stein is an Associate Professor within the Agents, Interaction and Complexity research group, which is part of Electronics and Computer Science at the University of Southampton. He completed his PhD in Multiagent Systems at Southampton in 2008 and he is currently a Turing AI Fellow. Sebastian's research focuses on techniques from mechanism design, incentive engineering, and sequential decision making, and their application for solving real-life problems in smart mobility, smart energy, crowdsourcing and cloud computing.

Alex S. Weddell received the M.Eng. (First Class Hons.) and the Ph.D. degrees in electronic engineering from the University of Southampton, U.K., in 2005 and 2010, respectively. He is currently a Lecturer with the Center for Internet of Things and Pervasive Systems, University of Southampton. He has over 15 years' experience in design and deployment of energy harvesting systems, and he has published over 70 peer-reviewed papers in the area. He is involved with three projects funded by EPSRC, EU Horizon 2020, and Clean Sky 2. His main research focus is in the areas of energy harvesting and energy management for future Internet of Things devices.

Martin Mayfield Martin is an engineer with design and research expertise spanning systems engineering, sustainable design, climate change mitigation and adaptation, mission critical and city systems. His work is focused on the pursuit of sustainable design solutions that balance complex engineered systems with nature.

He is currently the Infrastructure Research Leader for Engineering at Sheffield. He co-leads a group of 20 researchers working across the nexus of technology and infrastructure to enable the creation of a built environment that allows humanity to thrive within the carrying capacity of the planet. He has a grant portfolio of over £50m comprising both research, network and capital grants. His current work is focused on how to automate the process of retrofitting buildings to achieve the net zero target, urban air quality and delivering the Smart City agenda at low cost.

Mayfield had 24 years practicing as a designer of engineering systems at Mott MacDonald and as a Director of Arup. These roles entailed leading large teams of professional Engineers from a range of disciplines, working on a diverse array of projects in the UK and overseas.

Steve Beeby received a B.Eng. (Hons.) degree in mechanical engineering from the University of Portsmouth, Portsmouth, UK, in 1992, and the Ph.D. degree in MEMS resonant sensors from the University of Southampton, Southampton, UK, in 1998. He was a Principal or Co-Investigator on an additional 18 projects and has coordinated two European Union research projects. He is currently the Head of the Smart Electronic Materials and Systems Research Group. He leads the UK's Energy Harvesting Network. He is currently leading three UK funded research projects. He is a Co-Founder of Perpetuum Ltd., a University spin-out based upon vibration energy harvesting formed in 2004, Smart Fabric Inks Ltd., and D4 Technology Ltd. He has co-authored/edited four books including Energy Harvesting for Autonomous Systems (Artech House, 2010). He has given 17 invited talks and has over 250 publications and 10 patents. He has an h-Index of 50. His current research interests include energy harvesting, e-textiles, MEMS, and active printed materials development. Prof. Beeby was the recipient of two prestigious EPSRC Research Fellowships to investigate the combination of screen-printed active materials with micromachined structures and textiles for energy harvesting and was also awarded a Personal Chair in 2011.