Unmanned Aerial Vehicles for Air Pollution Monitoring: A Survey

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***Abstract*—Unmanned aerial vehicles (UAVs) equipped with air quality sensors offer a powerful solution for increasing the spatial and temporal resolution of air quality data, searching and detecting emission sources, and monitoring emissions from fixed and mobile sources. Despite the numerous advantages of using UAVs, their use, however, presents several challenges that limit their broader adoption. For example, UAVs require efficient algorithms and components to minimize power consumption, the overall payload used on UAVs needs to be small to ensure optimal portability which poses limitations on the sensors that can be integrated with UAVs, and there is a need for specialized algorithms, e.g., for identifying and locating air pollution sources. Currently, most solutions for UAV-based air quality monitoring focus on specific challenges or demonstrating the potential of using UAVs, and there is a lack of comprehensive overview of the research field and its open challenges. In this article, we contribute a systematic review of UAV-based air quality monitoring, highlighting, and analyzing technical solutions and challenges, and identifying open challenges with the aim of providing a research roadmap for the path forward.**

***Index Terms*—Air quality sensing, Internet of Things (IoT), low-cost sensor, unmanned aerial vehicles (UAVs).**

I. INTRODUCTION

POOR air quality is linked to a wide range of diseases, affecting millions of people worldwide and making air pollution one of the grand health challenges of our time [1]. Air pollution-related problems are fueling deployments of *air quality monitoring* technologies, which provide means to assess the severity of the problems and measure the effectiveness of initiatives designed to tackle air pollution [2]. Traditionally, air quality has been measured by fixed ground-based monitoring stations [3]. While accurate, such stations are expensive to deploy and maintain, limiting the size of deployments and reducing the density at which air quality information can be collected [3]. The World Health Organization (WHO) recommends deploying one air quality monitoring station per square kilometer and the EU clean air directive similarly suggests (approximately) one station per 200 000 inhabitants [4]. Such a resolution is clearly insufficient for understanding issues stemming from poor air quality. While there are some solutions to increase the resolution of information, such as the use of low-cost sensors [5], [6], these only partially alleviate the issue as deploying, operating, and maintaining these solutions is equally laborious. Alternatively, manned aircraft and satellites can, to an extent, be used to supplement the resolution of information [7]. However, data collection at high altitudes is limited by air currents and physical barriers which influence the regions that can be monitored. Manned aircraft also provide a limited view of the altitude at which the pollutants reside, which is essential for understanding the dispersion and other effects of pollutants [8]. The limitations of current solutions, combined with the high cost of deploying and operating fixed monitoring stations, call for alternatives that can help increase the scale and resolution of air quality information.

Unmanned aerial vehicles (UAVs) that carry low-cost air quality sensors (observing, e.g., gaseous pollutants, such as carbon monoxide (CO), CO_2, SO_2, O_3, or particulate matter density, such as $PM_{2.5}$ and PM_{10}) are emerging as a powerful solution for increasing the scale and resolution of air quality sensing as they can cover large areas rapidly [9], [10]. Beyond facilitating large-scale data collection, UAVs also offer new opportunities for atmospheric studies that help increase our collective understanding of pollutants [11]. For example, UAVs can be used in environments with different air pollution profiles to sample the vertical air column, allowing 3-D mapping and modeling of pollutants [8], [12], [13]. UAVs are also used to identify so-called fugitive emissions and to localize the source of emissions [14]. Fig. 1 illustrates the potential of UAVs by highlighting their use in smart cities to monitor areas with different air pollution profiles, including residential and construction, harbor, vehicle emission on roads, and industrial areas.

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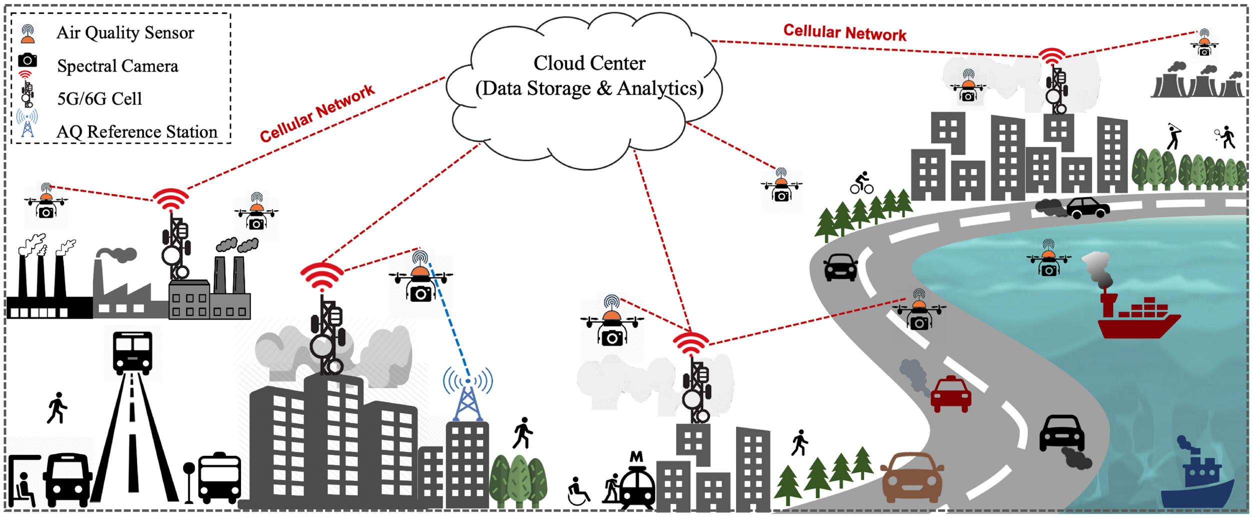

Fig. 1. Air Pollution monitoring using UAVs within a city with different air pollution profiles, such as residential, vehicles, harbor, and industrial areas.

TABLE I
EXISTING RELATED SURVEYS

Scope	Survey
UAVs and Air Quality	Applications of UAVs in air quality monitoring [7], [15] UAVs in remote sensing [16]–[18]
Air Quality Sensing	Low-cost sensing for air quality [5], [19]
UAVs	Communications [20] Specific tasks, e.g., navigation, control etc. [21], [22] Use of UAVs and regulations [23]

We contribute a systematic review of UAV-based air quality monitoring, analyzing technical solutions, highlighting different application areas, and identifying open challenges. Existing surveys (see Table I) have either focused on covering different application domains for UAV air pollution monitoring or on techniques addressing specific UAV challenges without providing a comprehensive overview of the field or the existing research gaps. Indeed, despite the many benefits of UAVs, their use currently is not widespread. This is due to the many challenges in adopting UAVs for air quality monitoring. For example, UAVs require efficient algorithms and components that minimize energy consumption. At the same time, the sensors that are integrated into the UAVs need to be inexpensive and sufficiently small to minimize overall payload size. This poses limitations on the quality of the sensors, and the information they provide. UAVs also need to be integrated with specialized algorithms, e.g., for controlling the sampling of air quality information and locating pollution sources. We critically review the research landscape to highlight challenges and to identify research gaps with the aim of serving as a catalyst for future research and establishing a roadmap for the path forward.

II. Scope of the Survey and Use Cases

A. Related Surveys

Table I summarizes existing surveys that partially overlap with our work. Existing surveys on UAVs and air quality monitoring have largely focused on covering different application areas and uses for UAVs without examining the technical challenges stemming from the integration of air quality monitoring into UAVs [7], [15]. Beyond air quality monitoring, there have also been surveys on the use of UAVs in different remote sensing tasks [16], [17], [18] but these similarly mostly focus on different application areas rather than on examining the field as a whole and analyzing the technical challenges associated with the use of UAVs. In the context of air quality monitoring, UAVs necessarily need to integrate low-cost sensors to ensure the cost and size of the payload remain feasible for long-term operations. Both the technical challenges of using low-cost sensors [5] and the different application areas have been covered by surveys [19] but these surveys do not consider issues relating to the use of UAVs. Finally, there are several surveys on UAVs and specific functionalities, such as navigation, control, and path planning, but these focus on UAVs more generally instead of discussing challenges stemming from their use to support air quality monitoring [20], [21], [22], [23]. Our work addresses the gap in existing surveys by providing a comprehensive review of the technical challenges, solutions, and research gaps emerging from the integration of air quality monitoring onto UAVs.

B. Selection of Articles

Using UAVs for measuring air pollution is an interdisciplinary topic, combining computer science and atmospheric sciences. We determined which articles to include (and exclude) from our survey through a two-phase process. First, an iterative search strategy was used to determine potentially relevant articles to include in the survey. We identified an initial set of articles using searches with a set of seed keywords on Google Scholar, IEEE Xplore, ACM Digital Library, and ScienceDirect. The following seed keywords were used: *UAVs, drones, drone swarm, low-cost sensors, sensor calibration, UAV communications, UAV networking*, and *UAV power management*. The initial set was then expanded by, including prominent articles that were cited in the papers, or that cited the papers. The papers were then briefly examined and labeled

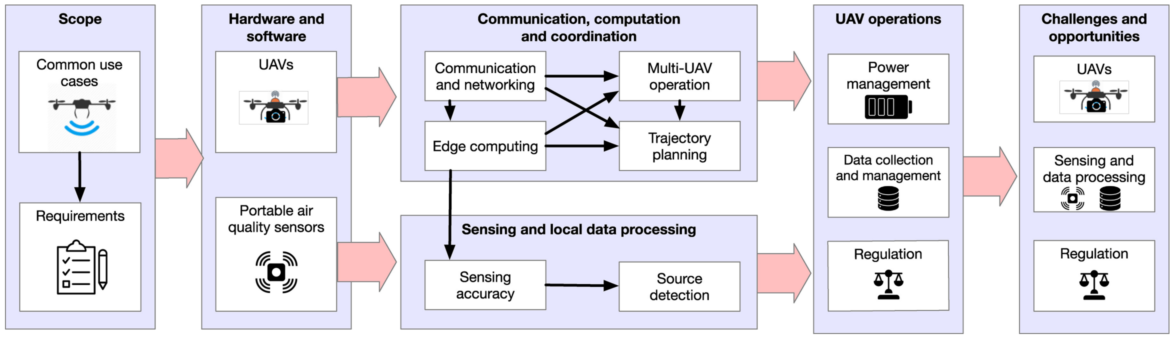

Fig. 2. Scope and structure of the survey. Arrows denote dependencies between the items.

as relevant or irrelevant depending on whether they relate to the topic and scope of the survey. Finally, the papers labeled as relevant were read by one or more of the researchers and this article was integrated into the survey.

C. Common Use Cases and Their Requirements

UAVs are capable of gathering high-resolution air quality data on particulate matter, carbon dioxide, volatile organic compounds (VOCs), and other harmful gases over wide spatial and temporal scales. In this section, we briefly present some potential use cases and the requirements they set for UAVs and their sensor systems.

Urban Air Quality Assessment: UAVs can be employed to assess the air quality of urban areas, helping to identify potential pollutant sources and hotspots. They are particularly useful in places where traditional monitoring stations cannot be easily installed due to urban infrastructure or spatial constraints [7], [15].

Industrial Emission Monitoring: A key benefit of UAVs is that they can monitor emissions from difficult-to-reach areas, including factory and ship smokestacks, offering the possibility of real-time pollutant detection and quantification. UAVs can also be used for monitoring remote and hard-to-access sites, such as offshore oil and gas platforms [24].

Forest Fire Tracking: UAVs can provide real-time data on smoke plume characteristics during forest fires. This information can assist in managing fire response strategies and predicting the impact on air quality in neighboring regions [25].

Volcano Emission Monitoring: UAVs equipped with gas sensors can monitor volcanic emissions, including sulfur dioxide and other volcanic gases, which can be hazardous to human health and aviation safety [7].

The above use cases are examples that demonstrate the potential of adopting UAVs for air quality monitoring. Realizing these applications, however, also sets specific requirements for UAVs and their sensors. First, sensors need to be lightweight, energy efficient, and cheap considering the limited payload and power capabilities of most UAVs. Second, they need to have high sensitivity and selectivity to detect target pollutants at low concentrations or amidst a complex mixture of gases [3], [26]. Third, sensors must offer fast response times to ensure real-time monitoring and data acquisition. Some applications, such as tracking pollutant dispersion or identifying emission hotspots, require swift detection, and response to dynamic environmental conditions [15].

In addition to the sensors, the communication systems in UAVs must be robust and reliable to ensure timely data transmission, particularly during long-range missions or in complex terrains. Furthermore, these systems should provide a secure data transmission channel to protect the integrity and confidentiality of the collected data [27]. Finally, UAVs and their sensors should be resistant to harsh environmental conditions, such as high temperatures, high altitudes, or corrosive atmospheres, which can be encountered in applications like forest fire smoke tracking or volcano emission monitoring. Thus, the selection of suitable materials and protective casings is of paramount importance [28], [29].

D. Survey Structure

UAV-based air pollution monitoring is a real-world example of Internet of Things (IoT) applications, and thus we structure the survey following a typical IoT architecture. Specifically, based on the common use cases and their requirements discussed in Section II-C and as depicted in Fig. 2, we begin the survey in Section III by covering hardware and software aspects, separating between the UAVs and air pollution sensors. Based on the hardware and software layer of the UAVs, the following section then covers the communication, computation and coordination layer, focusing on networking and edge computing as well multi-UAV operation and trajectory planning (Section IV). Here, the communication and computation aspects provide a solid ground for further discussion on edge computing, which are both prerequisites for the topics on coordination.

Respectively, the hardware and software layer of portable air quality sensors leads to a treatment on the sensing and local data processing layer (Section V), covering subjects, such as sensor accuracy (which is affected by edge computing) and subsequent source detection.

In the UAV operations Section VI, we further discuss UAV power management, data collection and management, as well as regulatory aspects, followed up in Section VII with open challenges, opportunities, and research directions for the future. Section VIII finally concludes this article.

III. Hardware and Software

A. Unmanned Aerial Vehicles

UAVs can be classified as civilian or military based on their capabilities, such as weight, size, and payload [30]. For example, while UAV weight can vary from less than 1 kg to up to two metric tons, those with less than 5 kg of mass are considered civilian UAVs [31], [32]. Due to their design and capability for mounting additional devices of up to a few kilograms, civilian UAVs are the best candidates for air pollution monitoring, as the weight of sensor devices and batteries does not often exceed the limit for civilian use [33], [34], [35]. Moreover, civilian UAV software is often open source, which allows improving their operational performance.

Quadrocopters combine stability and good maneuverability with a simple configuration. They can hover as well as take off and land vertically [36]. In addition, their size, weight, navigation system, energy storage, and communication and control systems allow using them in hazardous environments [37]. Depending on the number of batteries and the type of UAV application (sensing, communication, and processing), the flight time of UAVs may vary between 20 min to 2 h [38], [39]. As the energy requirements of air pollution sensing are not excessive (e.g., in comparison to other resource-demanding applications such as surveillance), their flight times can be long.

Advances in the UAVs' software enable the operators to plan reliable trajectories with minimal risk of collisions and to optimize paths for minimizing power consumption [40]. The latest drones also integrate self-healing mechanisms that ensure the UAVs can land safely in case failures or disruptions occur. The software can also provide limited autonomous flight capability for UAVs without the need for a pilot in local proximity, and even without satellite positioning. This also offers the drones a capability to safely return to their original locations even when network connectivity is lost [41].

B. Portable Sensor Devices

Air quality sensors are typically attached as a separate payload which must be sufficiently lightweight for the UAV to carry. Portable and lightweight air quality sensor designs are thus preferred, with a small form factor for easier mounting. Such sensors typically cost between $100 and $10.000, a low cost compared to professional grade air quality monitoring stations which typically cost a million or more [3], [26]. Low-cost sensors can offer high-density deployments, increasing the spatiotemporal resolution of air quality data [2], [42]. They have been used, for example, with urban infrastructure (e.g., light poles and public transportation vehicles) to capture air pollutants sourced from traffic and vehicle emissions [43], [44], or by maritime authorities to detect ships that violate international standards limiting the maximum sulfur content in marine fuel [45]. Moreover, due to their low weight, mobile sensors can also be carried by citizens for detecting air pollution hotspots in cities [3], [46].

Generally, low-cost air pollution sensors can measure gas pollutants and particulate matter, as well as meteorological variables, such as temperature, humidity, pressure, and wind [47], [48]. Gas pollutants include gaseous compounds, such as ammonia (NH_3), carbon dioxide (CO_2), CO, dimethyl sulfide (CH_3), hydrogen sulfide (H_2S), methane CH_4, methyl mercaptan (CH_4S), nitrogen dioxide (NO_2), nitric oxide (NO), ozone (O_3), sulfur dioxide (SO_2), and VOCs with all units in ppm; and particulate matters PM_1, $PM_{2.5}$, and PM_{10} with all units in $\mu g/m^3$ [9]. The sensors may also include processing units, local data storage, networking interfaces, and power sources [49]. The sensors can typically operate between the temperatures -20 °C and $+45$ °C, allowing their use in many climates. While the weight of each sensor device is usually less than a few hundred grams, they can be powered by additional portable batteries with each battery offering, for example, 3.6 V/3400 mAh. Depending on their operations, measurement frequency, and sensor configurations, the sensors can typically operate from 2 to 8 h on battery support [48]. While portable sensor devices are laboratory calibrated when manufactured, they often have low accuracy and high drift variation in field measurements [42]. Therefore, these sensors require periodic calibration to ensure they remain accurate and consistent [50], [51].

Cameras can potentially be also harnessed for air pollution monitoring. For example, the HD camera onboard a drone has been used to monitor haze from 360° aerial panoramic images [52]. By taking these pictures from multiple directions (six in the case of the study in question), it is possible to estimate the overall air quality index at a location. As another example, the study in [53] addresses the potential of enabling devices with cameras to act as air quality sensors. This study utilizes a large data set containing 1000 photos to train a deep neural network that is used to estimate air quality, and shows 87% and 75% accuracies for day-time and night-time operations, respectively. Hyperspectral cameras also can be mounted on UAVs for air quality monitoring [54]. The hyperspectral images can be analyzed with machine learning and deep learning techniques [55] and enable detecting air pollutants, such as aerosols, e.g., $PM_{2.5}$ and gas, e.g., O_3 [56].

IV. Communication, Computation, and Coordination

A. UAV Communications and Networking

Emerging 5G (and beyond) networking technologies are essential for UAV communications, offering ubiquitous connectivity, ultrareliable and low-latency connections, and big data stream processing capabilities [57], [58]. The ubiquitous connectivity of these networks supports massive-scale deployments [59]. The networks are also expected to feature high data rates (even exceeding 10 Gb/s) and low latency. While common low-cost air quality sensors have moderately low data rates, pollution monitoring is increasingly harnessing more advanced sensors that demand high network bandwidth. Hyperspectral cameras are one such example as they can produce gigabytes of data per second [54]. Low latency, in turn, is a prerequisite for coordinating UAV deployments and ensuring sampling can cover the most relevant areas [12].

Communication networks for UAVs face several challenges due to the constrained resources of UAVs, the overall network architecture needed to support large-scale operations, and fast-changing mobility [20]. UAV networks are prone to changing fast and unpredictably, as the number of UAVs that join or leave the network varies over time and is highly dependent on the application scenario and the deployment environment. As such, the fluid topology of UAV deployments dictates special design criteria for the network architecture. Particularly, routing protocols need to reflect the continuous changes in the UAV backbone, where the network is prone to partitioning [20]. Partitioning, in turn, leads to another challenge, namely, transferring communication sessions from out-of-service (e.g., UAV leaves the network) to active UAVs. In doing so, special attention needs to be paid to the energy conservation of UAVs that remain in the network.

Energy expenditure in UAV systems relates directly to their weight, size, and their path trajectory (e.g., time of flight and hovering in the air). Joint UAV path planning is thus crucial for maximizing coverage and minimizing downtime in massive-scale deployments. Joint planning requires suitable network architectures. The simplest example is a centralized architecture where UAVs communicate among themselves and a UAV leader node. Such a leader node may serve the role of an orchestrator, disseminating the path trajectory to the rest of the nodes in the network, and communicating directly with a 5G station on the ground [60]. While vulnerable to failures, this approach helps to limit the energy expenditure of non-leader nodes as they do not need to switch on a power-hungry long-range radio interface (e.g., 5G) to communicate with the ground. Alternatively, the UAV system may employ a layered architecture where the swarm self-organizes into layers based on their capabilities [61]. Specifically, UAVs of higher communication and battery capabilities could monitor an area of interest from a high altitude, and thus identify areas where there is a need for UAV drone presence, whereas nodes of lower capabilities are delegated with sensing tasks in such areas.

UAV-based networks have gained traction, especially within the 5G context [62], either accessing the existing communication infrastructure or complementing it in case of disaster scenarios. Any UAV-based communication network should be flexible enough to support multiple applications and diverse requirements [57]. The energy expenditure of the network can be optimized using realistic 2-D and 3-D mobility to minimize their flying and hovering time, and thus to save energy. UAVs achieve their highest throughput when they hover (i.e., are stationary) above the ground terminal (GT) as this allows maintaining stable channel conditions. However, hovering is highly inefficient for rotary-wing UAVs and impossible for fixed-wing ones. Instead, a circular trajectory, centered at the GT, can optimize both energy expenditure and communication throughput [63]. Dynamicity of the network, i.e., the support for UAVs joining or leaving the network, in turn, can be implemented by considering a layered topology where a mesh or ad-hoc network topology connects the UAVs with each other, and a separate star topology connects the individual mesh/ad-hoc components with a leader that communicates with a control station. In cases where centralized control is unavailable, such as disaster scenarios or remote areas, UAVs can be deployed in a multi-UAV scheme to provide ad-hoc aerial base stations at which users on the ground can connect to [64], [65], [66].

Beyond the network architecture, communication security remains a big issue for UAV communications [67]. For instance, blockchain and AI can be used to secure UAV communications from possible cyber-attacks without the need for centralized infrastructure. While these solutions promise good security and privacy features, they incur high transaction storage costs, and on-board power and computational resources, which UAVs lack. As such, both AI and blockchain-based solutions need to be tailored to consider the resource constraints of UAV-based networks [68], and further research is needed to tailor these solutions for the needs and limitations of UAVs.

B. Edge Computing

Edge computing is anticipated to play a pivotal role in delivering efficient computing services across a wide variety of applications within smart cities. As a major paradigm shift, edge computing is projected to be integrated within cities, working alongside the emerging 5G and 6G networks. This integration is aimed at ensuring ubiquitous connectivity, facilitating massive IoT connections, providing low-latency communications, guaranteeing high bandwidth, and managing data alongside real-time analytics [69], [70], [71], [72].

In the context of UAVs, these functionalities support an array of UAV-based applications, such as air pollution sampling, varying in frequencies, data rates, and from different locations and altitudes. Crucially, in UAV operations, transmitting data to edge nodes is essential due to the constrained energy budget and limited memory and storage resources of the UAVs. This limitation prevents the execution of computations onboard the UAVs and necessitates the offloading of computational and storage tasks to edge computers. Consider, for instance, the use of low-cost air quality sensors with UAVs, where a higher sampling rate would be desirable. Conversely, when employing hyperspectral cameras onboard UAVs (specifically to capture detailed hyperspectral air images), a higher bandwidth and data transmission rate becomes imperative. In the former scenario, the needs are primarily for data storage and real-time analytics, while the latter demands significant processing power. In both cases, the capabilities of edge computing are well-suited to fulfill these requirements [54].

Currently, numerous studies exist within academic literature that emphasize the importance of edge computing for UAV operations. For instance, a UAV-assisted target tracking system can capture high-resolution images for the optimization of the UAV's flight path [73]. These images are then offloaded to edge nodes for processing. The research further defines a cost minimization problem for the optimization and suggests an algorithm to distribute the UAV's tasks. The primary goal is to jointly optimize the UAV's operational time and energy consumption. This is achieved by carefully selecting edge nodes and assigning tasks based on each node's computational capabilities.

Several other studies envisage UAVs as aerial mobile edge computing platforms, capable of performing processing tasks for IoT devices located on the ground [74]. This framework proves most effective when the requirement involves delivering communication and computing services in remote locations or for temporary deployments, in, for example, disaster management scenarios. For example, drone-mounted base stations (DBS) may facilitate edge computing on the UAV itself to provide services [75]. This research frames a joint problem of user association bandwidth and computation resource optimization, aiming to maximize the DBS service time and task completion rates. Subsequently, the study illustrates the successful execution of such DBS communication and computation services.

Another approach in UAV-based edge computing involves creating an aerial edge computing network, where UAVs establish a network and share processing tasks amongst themselves [76]. In more detail, there are four network architectures in which UAVs cooperate to execute processing tasks [77]. A software-defined network architecture comprised of three layers, namely, data, edge, and relay, enhances the UAV network's scalability and controllability using smart function tables.

Due to the energy limitations of UAVs, several studies propose offloading computational tasks to ground-based edge computing nodes. To this end, UAVs may utilize 5G networks and employ vision-based navigation (that is, use camera images for navigation) [78]. The UAV may then evaluate whether to process the images onboard the UAV, fully offload them, or partially offload the image processing tasks to the edge nodes. The optimal decision is influenced by the network quality, such as the available uplink bandwidth and the computational capabilities of the edge server. Similarly, UAV applications may require video analytics, such as surveillance. A hybrid approach involving both ground-based edge computing and onboard UAV computing can conserve bandwidth without adversely affecting accuracy or latency [79].

C. Multi-UAV Operation

Localizing emission sources is a key task for large-scale environmental monitoring. Indeed, air pollution monitoring requires the identification of gas leaks and other sources of pollutants, which might occur over a vast area [80], [81]. The task of localizing and monitoring pollutant emissions typically leverages a fleet of drones, i.e., a swarm formation that requires the creation of flying ad hoc networks (FANETs) and formulation of a stable network structure [82]. Indeed, the successful operation of drone swarms relies heavily on effective communication, collaboration, and collective decision making. As such, most research [83], [84] focuses on algorithms that optimize the paths of drones in a swarm to ensure continuous communication among drones, and thus synchronize their sensing efforts into a cohesive target plan. These works are usually evaluated in constrained testbeds or simulations and adapting them to challenging real-world environments is far from straightforward. Most of the algorithms assume unhindered search space where the drones can move freely and assume a central coordinator is responsible for optimizing the movements of the different drones. For example, the survey in [82] presents different distributed gateway-selection algorithms (where a drone is selected as a gateway) as well as cloud-based stability-control methods to efficiently perform multi-UAV operation tasks.

In practice, obstacles, weather conditions, and other factors mean that drone swarms need to coordinate movements among themselves and adapt to changes in the environment. Most drones are also heavily energy constrained, which limits the resources they have available for making decisions. Overcoming these challenges requires systems and algorithms that account for these challenges.

Drone base stations (DBSs) are often considered a viable and dependable approach to complement or replace existing communication infrastructure. Operation of drone swarms—and other types of multi-UAV systems—builds on top of swarm intelligence which focuses on optimizing the locations of drones in a 3-D space [85]. Designing path trajectories and UAV placement algorithms calls attention to system resilience and self-regulation of the underlying network coordinating the swarm. For example, a leader UAV can be remotely controlled by a pilot on the ground, and the remaining drones can then regulate their location to stay within communication range with the leader by using signal strength measurements to assess the distance from the leader drones [86]. Similarly, a controller may organize the drones to fly in circles at different heights while ensuring communication among them [87]. This works best on smaller drones, such as tri-rotor drones, which are highly flexible and able to maneuver in small areas. The latter is critical for many air pollution sensing scenarios as it enables drones to reach closed areas, such as buildings, tunnels, or pipes. Drone swarms are often heterogeneous which means the drones can support different communication ranges. Maintaining communication distance between the drones requires careful consideration of their organization, e.g., by using clusters to coordinate specific sets of drones to reduce the risk of drones disappearing from the network [88]. One example of the use of drone swarms is gas sensing in industrial environments [89].

Air pollution sensing within an FANET is challenging as the swarm network must be resilient and able to update the path of drones or the overall formation on-the-fly in case of unexpected disruptions, e.g., hitting obstacles or a drone battery depletes [90]. Indeed, network creation in an FANET has a significant impact on the efficiency of multi-UAV systems. Therefore, to obtain an effective multi-UAV operation, an FANET needs to be incorporated into the software framework that is responsible for planning and coordinating the drone operations as well as the load balancing between UAVs. A potential solution is to use software-defined networking (SDN) within an FANET. Indeed, while SDN enables obtaining information about the state of UAVs, it allows collecting information on the architecture and topology of FANET. For example, the study in [91] proposes an SDN architecture for load balancing in an FANET. Thus, the proposed SDN enables collecting the topology and link-state information among UAVs using the SDN controller, and it allows collecting battery information from the UAV controller. Using the collected information, then the proposed SDN solution balanced the load by directing the load to UAVs with a higher amount of battery.

Another option is to incorporate separate planners for the overall mission (global mission planner or GMP) and the individual drones (agent mission planner or AMP) [92]. The former assigns and monitors missions, which consist of different individual tasks. The latter, in turn, manages the tasks assigned to individual UAVs. This type of architecture enables flexible and dynamic planning of missions in domains where human intervention is not possible. Examples include automatic target detection and identification, and search and rescue operations [66]. Drone swarms deployed in critical situations, such as disaster scenarios, also pose specific requirements in terms of latency and communication stability. Mobile networks, and especially LTE, are generally considered the most reliable network interface for drones to communicate in such an environment [93]. While LTE delivers the highest communication range and data rates, it suffers from high energy expenditure. In scenarios where energy is the main priority, LoRA tends to be the best option. When possible, data should be offloaded to a third party for further analysis, e.g., edge or cloud server, as this mitigates the energy expenditure.

Optimal path planning is another factor for helping to contain energy drone expenditure [65], [94], especially crucial during disaster scenarios. Drones should be able to follow their intended path even if communication with the controller (or operator) is lost regardless of whether the drones operate individually or as part of a swarm [95]. For instance, drones in a multi-UAV platform may complete their mission with the use of predownloaded maps, in the event Internet connection is lost [96]. Moreover, in hostile environments, such areas are highly polluted with recent contamination, and multiple operators may direct their drone swarms to the location, requiring a strategy to detect and localize their own drones among the many operating ones [97]. Such a strategy may help in tracking drones and guiding them into carrying out their mission.

D. UAV Trajectory Planning

Planning the path or flight trajectory of UAVs requires considering multiple objectives simultaneously. For example, ensuring sufficient coverage may require simultaneously collecting sensor measurements from many locations whereas ensuring long-term operation requires minimizes the amount of data that is being transmitted per drone. Sensor readings may also have deadlines, e.g., gas measurements may disperse over time or pose an instant health risk making it critical to collect and analyze them sufficiently fast. The appropriate techniques also depend on the deployment environment, e.g., in a smart city the UAVs may combine their own measurements with readings from static sensors that are deployed into the environment. In this case, the trajectory of the UAVs needs to be designed to account for the other available readings, especially if there are deadlines regarding the usefulness of the information [98]. Path planning also needs to consider potential obstacles and application-specific criteria. For example, the speed of convergence and overall efficiency are critical for pollution source localization [99]. The techniques that are used for optimizing the path typically build on multiobjective optimization approaches, either formulating an optimization function [98], [100] or using learning the optimal function over time, e.g., using reinforcement learning [101] or heuristic optimization strategies [102].

The main objective of optimizing the UAV's trajectory is to achieve improved performance with optimal UAV trajectory, for example, to generate optimized flight trajectories to increase object detection performance and optimize energy consumption. The overall interest is also to maximize the number of tasks to be completed by the UAV or the number of services to offer to the users (either IoT nodes on the ground or other mobile objects). To formulate the optimization functions, generally, there is a need for a system model which includes the UAV's travel distance, the UAV's speed, and the distance between the UAV and the location of the users. The system model also considers the data transmission power of the UAVs which requires channel a model depending on the environment, e.g., urban areas where the UAV flies. This is to consider the probability of outage that is caused by path loss and shadowing in the environment [39]. For example, the research in [98] aims to jointly optimize the trajectory of a UAV while allocating radio resources to maximize the number of served IoT devices. To find an optimal trajectory, thus, this research considers a city environment and applies the Rician fading channel to model the communications channel. To find the optimal UAV trajectory, for example, linear integer optimization, or algorithmic approaches, e.g., ant colony optimization [100] is formulated and a set of constraints, such as the amount of energy to be consumed and the minimum number of IoT devices to be served is considered.

The other efficient approach for planning UAV's trajectory is applying reinforcement learning [101]. In practice, UAVs are highly mobile platforms and can fly in dynamic and uncertain environments with changing communication properties, such as shadowing in air-to-ground channels, path loss, and signal attenuation [103]. This feature of UAVs requires ensuring a sufficient quality of service and improved communications with either the ground control stations or with the other UAVs and communication nodes. Reinforcement learning enables the UAVs to optimize the real-time trajectory planning given outdated knowledge of the network states [104]. Reinforcement learning uses the principles of the Markov decision process such that at each time step, the environment is at a certain state, and each UAV chooses a certain action using its policy. When the environment transits into a new state, a reward is produced for each UAV to improve its policies [105].

In UAV trajectory planning, when utilizing heuristic optimization strategies, the UAV flight space is discretized and a search space is constructed. In UAVs path planning, each transition between the discretized locations has a unique cost, and the optimal path from an origin location to a destination location is the minimal cost across all possible paths [102].

When multiple UAVs are planned in tandem, the problem can be modeled with coalitional game theory and an optimum that is simultaneously the best for multiple UAVs can be found [106]. Applying the coalitional game when planning multiple UAVs in tandem first improves the UAV network stability and reliability as the coalitional game is a classic cooperative game theory that encourages individual UAVs to operate as an entity [107]. Second, using the coalitional game enables the UAVs to improve data offloading efficiency by aggregating the data [108], [109], [110].

Path planning forms the basis for determining UAV trajectories but in practice, there are further challenges that need to be considered. For example, UAVs flying over populated areas may pose a safety risk of malfunction and they may also be disturbing unless they are operated at sufficient altitude. Operating UAVs also generates noise which is a source of irritation to people. These issues may place additional constraints on path planning, e.g., the permissible regions are likely to be governed by geo-fences and other regulations. Maintaining operations within the designated areas also poses hardware and sensor requirements, requiring sensors that can efficiently monitor UAV position and tamper-resilient modules that prevent overriding the geo-fencing information.

V. Sensing and Local Processing

A. Sensing Accuracy

Lightweight sensors, especially those mounted onboard UAVs, tend to suffer from sensor drift and poor measurement accuracy [26], [42]. The poor accuracy is caused by meteorological factors, such as high temperature, humidity, and wind speed, as well as anthropogenic factors, such as intensive pollutant emissions, e.g., from ships or industrial sites [111], [112]. Maintaining sufficiently high and consistent accuracy requires calibrating the sensors, which can be accomplished using machine learning [5]. Examples of popular calibration methods include simple linear regression (LR), multivariate LR (MLR), linear mixed-effects models (LMMs), support vector machine (SVM), decision trees (DTs), random forests (RFs), k-nearest neighbors (KNNs), extreme gradient boosting (XGB), and artificial neural networks (ANNs) [113], [114], [115], [116]. Several studies have evaluated and compared ML-based calibration methods. Generally, the results have varied depending on the data sets but usually ANNs and methods combining multiple models, such as RFs and XGB, have achieved the best results [117], [118], [119]. Recently, there have been many approaches that build on deep neural networks. These range from models that comprise ensembles of regression models [120] to autoencoder models [121]. These approaches have shown promising results, but as with the other techniques, the performance depends on the characteristics of the data sets that are used for training and testing the calibration models. The performance not only depends on the characteristics of the data set but also on the pollutant that is being calibrated and the similarity between the data sets that are used for training and evaluating the calibration model [51].

Air quality sensors attached to UAVs are typically used in highly dynamic settings where wind speed, pollutant concentrations, humidity, and other environmental factors vary. In these situations, the best performance is typically obtained using in-field calibration that tailors the calibration model to the environment where it is being used. In-field calibration is currently a highly active research domain and a wide range of models have been investigated. For instance, Gaussian process regression (GPR) based in-field calibration of airborne particle sensors has been shown to yield considerable improvements in sensing accuracy [122]. Other studies have shown ANNs and other nonlinear techniques to generally yield the best performance whereas regression methods (LR and MLR) tend to be vulnerable to inconsistent behavior [42], [123].

Sensor calibration requires having a reference sensor that provides information on the magnitude of the sensor errors. Traditionally this is achieved by co-locating the sensors undergoing calibration next to a professional-grade station for a period. This approach naturally scales poorly to large deployments and requires access to a reference station [124]. Node-to-node (N2N) calibration and sensor network calibration are alternatives that seek to reduce the effort in calibrating the sensors by propagating the information from one or more low-cost sensors that are in proximity of reference stations to other sensors that have no access to a reference instrument. This approach has achieved highly promising results [50], [125] and is best suited for UAV-based sensors. The performance of these approaches can be further enhanced using so-called calibration transfer which adapts the calibration model by considering the similarity of the environments where reference information has been obtained and the target environment where the sensor is used [126], [127].

The most common way to perform sensor calibration is to learn a separate calibration model for each pollutant that needs calibration. An alternative is to take advantage of multisensor data fusion which allows capturing more complex dependencies between the sensors. As an example, multiple regression models that capture the cross-sensitivities of O_3 sensors have been shown to outperform a baseline approach [128]. Similarly, a nonlinear estimating model fusing multiple sensor data reduces calibration errors [129]. In addition, a sensor-fusion calibration technique recovers high-fidelity ambient pollution, including O_3 and indoor CO_2 concentration levels from human interference [130]. Multisensor data fusion thus not only improves sensing accuracy but can also help to maintain high accuracy when the sensors are adopted in new environments.

B. Air Pollution Source Detection

UAVs not only can help to monitor emissions but also identify and traverse to emission sources. This requires the UAVs to integrate algorithms that can localize the pollution source, which can be a fixed (i.e., a certain geographical location) or a mobile source (e.g., a ship). Pollution source localization traditionally takes advantage of optimization techniques with the most popular approaches being swarm optimization, engineering-based optimization, and bio-inspired optimization.

Swarm optimization relies on a coordinated swarm of UAVs that employ a coverage algorithm that plans the UAV trajectories to maximize the likelihood of finding an emission source, such as a gas pollution leakage in an industrial area [89]. Coordinating the movements of the UAVs participating in the swarm is crucial for maximizing coverage and making the detection of pollution sources faster. These techniques are not restricted to outdoor use but can equally well be applied in indoor settings. For example, multirobot search methods have been used to localize the source of odor in an indoor environment [131]. The optimization may also require external information, e.g., the odor detection example relies on airflow information within the environment, and most optimization techniques have some information about the layout of the area that is being monitored (e.g., in the form of a geofence). Cooperating swarm methods typically build on common optimization techniques, such as particle swarm optimization [132], genetic algorithms [133], or ant colony optimization [134]. Testing swarm cooperation in real-world situations is highly challenging and the use of simulations has been the most common way to evaluate different solutions.

Engineering-based approaches, in contrast, use physical or data-driven methods to estimate a pollution source distribution and to predict the most likely source locations. These approaches typically require a lot of hardware and energy resources from the UAV and are best suited for situations where the UAVs collaborate with other platforms that can provide the necessary resources (e.g., ground drones or a separate control unit). As an example of an engineering-based approach, a probabilistic plume tracing method has been shown to be effective at allowing a mobile sensor network to effectively detect pollution sources in a time-varying airflow environment [135]. Engineering-based approaches require coordinating and planning the data collection to ensure they can estimate the overall distribution accurately. As an example, locations at different distances from the origin can be selected and measurements are then autonomously carried out at those locations to estimate the overall distribution and to trace pollutant sources [136], [137]. As these methods output a probability distribution over the target space, the output of these methods can also be visualized to support the identification of leaks and pollutants [138].

Finally, bio-inspired algorithms mimic the search strategies employed by living things (e.g., ants) to detect sources of pollution. Typically, a robot, such as a UAV measures pollution concentrations at two spatially separated locations estimates the concentration gradient and adjusts the search direction angle accordingly [139]. Alternatively, the UAV can use a discrimination index, an estimator, and a behavioral model to trace the pollution [140] or collect pollution data along a path with a given shape (e.g., a spiral) to calculate to assess the proximity of a pollution source [141]. In practice, such bio-inspired algorithms consider minimum input from the environment, such as wind flow, meteorology, and area mapping, which makes them incomplete and leaves open research questions when executing them for real-life air pollution source detection. For instance, meteorological variables are affected by the UAV's airflow [142]. Hence, UAV path planning should consider weather conditions when performing air pollution sensing. Indeed, air pollution concentrations are highly variable due to the mixing caused by weather conditions, such as wind speed and direction, or interactions between pollutants. Therefore, to perform accurate air pollution measurements, the UAVs require efficient search algorithms so they can continuously predict the emission source and autonomously plan new waypoints for flying.

VI. UAV OPERATIONS

A. Power Management and Energy Tradeoffs

Power management of UAV-based systems can be tackled from different perspectives. Generally, the breakdown of energy consumption in UAVs identifies three main contributors.

1) The energy fed to UAV's motor(s) and propeller(s) which enable UAVs to fly and maneuver.
2) The energy fed to on-board sensing devices (e.g., air pollution sensors and cameras).
3) The energy spent for communication among UAVs or between UAVs and a data collection entity (such as a GT).

The energy expenditure of a UAV is highly dependent on its size and weight, the number of propellers (in multirotor UAVs), the size and weight of on-board sensing devices, the type of mission (i.e., UAV's trajectory, sensing tasks, and duration of the task), the size of the on-board collected data that needs to be communicated to a GT, and parameters affecting maneuverability, such as maneuvering speed, weather, and wind [143], [144]. These factors account for nonlinear patterns in the energy consumption of UAVs, making the consumption challenging to model.

As UAVs enable a wide range of services [145], their functions, capabilities, and resources may vary drastically. UAVs deployed for air pollution or other sensing tasks often have multiple rotors. These multirotor drones (e.g., quadcopter, hexacopter, and octocopter) rely on propellers to transform rotary motion into thrust, which enables the UAV to fly and maneuver. Optimal rotor configuration in UAVs can lead to better aerodynamic performance, and thus decrease energy expenditure during propulsion and maneuvering [146], [147]. Indeed, a big tip distance (between rotors), a certain rotor height, and zero tilt yield the best aerodynamic performance. Minimizing rotor–rotor airflow interactions often means having fewer rotors with larger blades instead of a mixture of small and big blade rotors that might destructively interfere with each other [147]. The advantages of minimizing rotor–rotor interaction show also in terms of a higher quality of the data sensed by onboard sensors [148]. Specifically, a more compact and controlled air vortex resulting from rotor-to-rotor interaction is desirable to minimize the disruption of sensors. In the same vein, the installation of a short wing (*lifting-wing*) in multirotor UAVs can help lift UAVs, together with the rotors, at a smaller energy expenditure [149]. Tilting the lifting wing at a specific angle decreases resistance to the wind and increases yaw stability, which ultimately translates into a smaller energy budget for these operations.

Besides the design of the drone itself, the operations performed by the UAV can be optimized to mitigate energy expenditure. In air quality sensing, there is an intrinsic tradeoff between power drain and pollution sensing as better and more detailed information requires more effort from the UAVs [11], [150]. Once a UAV reaches a source of emission, continuous sensing, and measurement until the transmission of a reliable air quality data set is needed. However, increasing the duration of data transmission as well as the sampling rate negatively impacts the power requirement of the UAV. Hence, it is important to find an optimal duration for data sampling and transmission rates to keep the power consumption reasonable while ensuring a given level of data accuracy. The search for pollution emission sources often relies on visiting frequent waypoints, which increases the distance that a UAV travels and, as a result, its energy consumption. Therefore, it is necessary to intelligently detect optimal waypoints for UAV's flight considering the energy budget of the UAV and power requirements of other functions, such as sensing, UAV localization (GPS), communications, and processing.

Smart trajectory planning of UAVs is another factor that allows reducing energy consumption. Air pollution sensing with UAVs requires UAVs to scan an area of interest and hover over certain locations to acquire data via onboard sensors. This operation results in changing UAV's speed, direction, and propulsion energy to accommodate its trajectory [151]. Moreover, UAV fleets might experience UAV heterogeneity in terms of payload, operational time limit, and energy budget. As such, allocating tasks (e.g., sensing tasks) to UAVs with sufficient resources and appropriate technical specifications is paramount to ensure successful task completion. For instance, energy and delay-aware task assignment to UAVs—subject to their energy status, location, and onboard equipment—can improve system performance [38], [39].

Energy conservation operations might not be sufficient for critical operations that require a long operational time of UAVs (e.g., natural disaster scenarios [65]). Autonomous and wireless charging techniques for UAVs are at the center of many research works [152], [153]. UAVs must be able to update and optimize in real time their trajectory to include recharging points—UAVs must be able to reach such points before their onboard power budget runs out [152]. Alternatively, concentrated beams of light can be pointed at photovoltaic (PV) cells installed in UAVs to charge them [153]. The drawback to this solution is the fact that UAVs must be close to the source of light, which in turn could be dangerous for people's health. Another option is leveraging the high electromagnetic (EM) fields of high voltage power lines to wirelessly transfer power (WTP) to UAVs [154]. To this end, an optimal design of UAV coils for fast WTP is crucial. For instance, a wireless charging platform can achieve stable output power under dynamic coupling effects of the EM fields in the coils [155].

B. Data Collection and Management

Trajectory planning and scheduling are crucial for UAV data collection and optimally they are co-designed to ensure maximal efficiency. Instead of modeling the exact trajectory, a common approach is to approximate the path using a discrete set of waypoints and to associate the operations around the waypoints [156]. The energy expenditure of data collection can be further decreased by reducing the sampling frequency and using data reconstruction techniques, such as compressive sensing, to improve the quality, and coverage of measurements [157]. Data reconstruction techniques typically work best for data that exhibit spatial or temporal correlations, which is the case in air pollution measurements [51]. Further optimizations can be achieved by optimizing the communications protocol that is used for transmissions, e.g., by mitigating retransmissions caused by conflicts [109].

In large-scale deployments, UAVs are expected to work together with fixed sensor infrastructure deployed in buildings, vehicles, and other urban infrastructure. In these types of applications, it is difficult to plan data collection such that the location and status of all sensors are simultaneously considered. For example, the data collection of sensors should be coordinated to minimize redundancy and decrease power consumption. This may require decoupling different operations and having different schedules for different components. For example, sampling points can be determined along flight paths whereas the network interface can be woken up only when data is transferred from fixed sensors to the UAV [158]. Alternatively, the UAVs may focus on data transfer while flying, offloading data from the sensor network [159] or onboard sensors [160] to a cloud-based storage system for further analysis. Important concerns include power efficiency, the capability to compress data (particularly for high-volume modalities, such as video or hyperspectral images), and the delivery of important information about the drone [159]. Similarly, offloading data from the sensor network or onboard sensors to an edge node for future analysis may reduce power consumption on the drone itself [161]. While opportunities to harness edge infrastructure are currently limited, they are expected to increase in the near future as edge computing infrastructure is best suited for scaling up computing support for cities and other large-scale domains [71].

Data can also be stored on the drone until it returns to base where the data can then be analyzed. Note that this does not necessarily mean landing the drone as navigating it into the communication range of a ground station suffices. In some applications, the UAVs can even function as additional communication infrastructure. For example, during crowded events, air quality—and other IoT devices—may suffer from poor connectivity due to the base stations being congested. In these situations, the UAVs can link further base stations into the network and improve network connectivity [162].

Data management also encompasses the confidentiality, security, and integrity of the collected data. In the worst case, the consequences can even be fatal. For example, compromised air quality data could lead to a situation where the data falsely indicates that it is safe to travel while the air is poisonous. Another example occurs in pollution accounting where compromised data could underestimate the amount of pollution that is being generated and result in unsafe operations. Beyond standard security operations, such as authentication and tamper resilient components, the operations may need support from distributed storage and distributed ledgers, particularly when the interactions involve multiple stakeholders [163].

C. Regulation

Civilian applications of UAVs have drastically increased in recent years, leading to an increased number of UAV operations. For instance, already in 2018, there were more than a million UAVs registered in the U.S. alone. Approximately

83% of UAVs operate at altitudes of 120 m or below [164]. The increasing number of UAVs operating at low altitudes may cause damage to terrestrial and urban infrastructure, cause security threats, and may disrupt people's safety and privacy [34]. For instance, UAVs may be used for criminal activities, to breach privacy, to plan and execute cyber-attacks, and even to smuggle drugs. Uncontrolled usage of UAVs can also cause mid-air collisions with civil aircraft as traditional radars, which are used to capture medium to high altitude air traffic, are unable to locate UAVs flying at such low altitudes [164]. Such collisions can lead to loss of life and property, whereas collisions with terrestrial property can damage transport and other urban infrastructure [165], [166]. UAVs could potentially also be used against military or other safety-critical operations, causing serious security breaches. For instance, GPS spoofing can manipulate UAV GPS coordinates and divert it to areas that are geo-fenced, thus enabling malicious tasks [167]. Besides, a technical glitch in a UAV could lead to its collapse, along with the machinery that it carries.

To overcome risks from unsafe or malicious uses of UAVs, many countries have started to draft rules and regulations for UAV operations to limit or avoid their misuse (e.g., operating drones over government or military spaces, nuclear and other strategic spaces) [34]. Current traffic management regulations state that a UAV must fly within the airspace and time slot allotted to it. The allotted airspace and time slot should not be in conflict, and there should be measures that prevent UAVs from crossing geofencing defined by governments [168], [169]. UAVs deployed for air pollution monitoring should follow the most recent regulations [170] which also means that the control software needs to be regularly updated to account for potential changes. Beyond regulation, training, and certification are seen as important tools for improving the safety of UAV operations [171]. For example, in the U.S. different licenses and certifications are being introduced in the U.S. to provide training on secure and safe operations for UAV operators [172].

The rules and regulations defined for UAVs mainly focus on keeping air traffic safe for the public [23]. In the future, separate provisions that cover uses that are beneficial to society, such as air quality monitoring, are needed. Alternatively, air quality monitoring could operate as part of other special provisions, e.g., by leveraging package delivery drones. In the U.S., the regulations governing the operations of UAVs are based on the regulatory recommendations of the federal aviation administration (FAA), which state that:

1) small UAVs must be operated in line of sight;
2) UAVs should not be operated directly over an individual or any moving vehicle;
3) the speed of operation should not exceed 100 mph [173];
4) any UAV which lies within the 0.55 to 55 lbs weight category should be registered;
5) UAVs must fly below 400 feet;
6) not operate any UAVs within 5 miles of any airstrip [167].

In Europe, in turn, the regulations are set by the EU aviation safety agency (EASA), and they fall within the single European sky (SES) initiative which aims for a high level of safety in the civil aviation sky [174]. The regulations are planned to take effect during 2023 and address security, safety, and privacy concerns involving, for example, UAV registration and UAV radio communication. The drafted regulations are mostly based on a risk-factor approach, market integration expectations, and the involvement of UAV sector agencies and organizations. The regulations allow member states to lay down national regulations in addition to the overall EU-wide foundation which needs to be implemented regarding border safety or national security [175], [176]. While these restrictions are in place to protect people and safety-critical operations, they may also restrict and cause difficulties for UAV operations. For example, path planning needs to avoid sensitive areas and operate within the regulations, and data collection schedules need to be designed with these constraints in mind. In the near future it may be possible that some parts of the airspace are designated for applications that are beneficial, e.g., low-altitude air corridors have been evaluated in China [164].

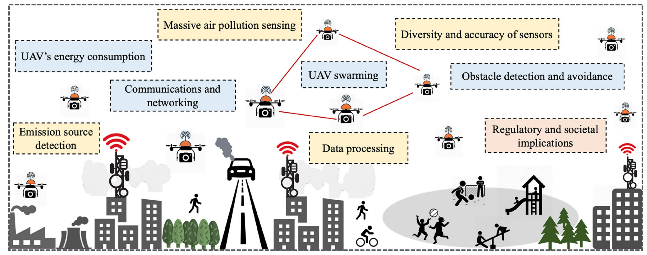

Fig. 3. Challenges and opportunities related to UAV-based air pollution sensing.

Current regulatory frameworks focus on the operations of the UAVs but at the same time it is important to note that air pollution monitoring integrates data collection and processing as part of the UAV operations, and these tasks are typically governed by separate regulations. Ensuring these regulations are also satisfied is critical as otherwise UAVs may unintentionally—or even maliciously—breach the privacy of individuals and businesses. This means that any personal data collected by UAVs, such as photographs and locations, must be protected [165] and that the storage and processing of data should abide by the appropriate privacy laws and guidelines [172], such as the GDPR in the EU.

VII. Challenges and Opportunities

In this survey, we have provided a comprehensive survey of different UAV techniques that are needed for enabling the large-scale use of UAVs for air quality monitoring. We next reflect on our survey and highlight research directions for future work. We discuss these from three perspectives: 1) UAV technology; 2) sensing and data processing; and 3) regulatory and societal implications. The challenges are summarized and contextualized in Fig. 3.

A. UAV Technologies

Obstacle Detection and Avoidance: Air pollution sensing is expected to operate in different environments, such as built environments, along roads, harbors, and green areas. These environments have distinct characteristics, yet each integrates obstacles (buildings, trees, cranes, etc.) that must be avoided and considered as part of path planning. At the same time, the environments and the obstacles may affect the onboard sensors of UAVs and hamper the use of specific sensors, e.g., mislead or cause blackouts in GPS signals. Further research is needed on path planning and obstacle detection approaches that can operate in diverse environments, and there is also a need for testbeds and experiments on the performance of sensors and algorithms in real-life target environments.

Swarming: The use of UAV swarms for monitoring can provide several benefits, such as higher coverage, improved sensing accuracy, and faster data collection. UAV swarms can work together to cover a larger area and can provide a more comprehensive view of air pollution levels. In addition, UAV swarms can cooperate to perform specific tasks such as emission source detection. The coordination and control of UAV swarms are highly challenging and require advanced algorithms and communication protocols. Mechanisms for UAV swarm coordination have long been an active research area but further research is needed to extend these works to operate in heterogeneous environments, e.g., where the UAVs coordinate with sensors that have a fixed deployment or where UAVs with highly different capabilities—or even different air quality sensing capabilities—cooperate.

Energy Consumption: Air pollution sensors differ in their sensing capabilities and thus differ in the technologies and energy requirements that they need to consume. The power limitations and allowed weight of a UAV can affect the energy consumption of the sensors and need to be considered in the design of UAV-based air pollution monitoring systems. Air quality sensors also pose requirements on the integration with the UAV, e.g., air should be sampled outside of the drone downwash and the sensors should not be placed close to any components that heat up as the performance of the sensors often depends on temperature, wind speed, and other environmental factors.

Communications and Networking: UAVs operate in 3-D space which is an important application domain for optimizing communication infrastructure and testing network performance. Air pollution measurements using UAVs require flying the UAVs in environments that require sufficiently long-range, particularly if the UAVs operate autonomously instead of line-of-sight by an operator. Emerging technologies, such as 5G networks provide a starting point for communications, targeting ultrafast, ultralow latency, and high-capacity communication links that enable reliable communication for UAVs in cities. However, the reliability and suitability of these networks for large-scale UAV deployments need further validation, and the energy efficiency of the communications must be optimized to ensure maximal operational time.

B. Sensing and Data Processing

Sensor Diversity: Air pollution sensors come in different types and sensing capabilities and typically can measure meteorological variables, different gases, and aerosol pollutants [5]. The exact form of sensors depends on the application scenario with gas leakage scenarios focusing on VOCs and air quality monitoring focusing on pollutants that are part of air quality indexes. In practice, integrating all sensors on each UAV may be challenging due to cost, payload weight, or other design restrictions. Examples of other design restrictions include the difficulty of providing unobstructed airflow and cross-sensor interactions that can decrease sensor performance. Ensuring sufficient coverage and accuracy of information requires designing sampling schedules that consider restrictions in sensor availability. Alternatively, it may also be possible to use algorithmic techniques to overcome such variations in sensor availability. One example is the use of data reconstruction techniques, and another possibility is to harness virtual sensing which uses machine learning to predict the values of missing sensors using other variables [177].

Sensor Accuracy: The accuracy of air pollutant measurements is an important design consideration. In practice, the cost and payload restrictions mean that UAVs are more likely to carry low-cost sensors rather than professional-grade sensors. Low-cost sensors are prone to errors and thus there is a need to calibrate the sensors periodically [5]. Optimally the calibration would be conducted opportunistically [2], e.g., by periodically co-locating some UAVs close to a reference station and using machine learning to capture a compensation model that can mitigate errors. Achieving this at a large-scale requires further research, e.g., in path planning to enable paths that ensure the UAVs are co-located with professional sensors, and in sensor calibration techniques to facilitate transferring the model from one UAV to other UAVs that are located in areas with different weather and other environmental conditions.

Data Processing: While there are many applications that do not require real-time access to pollutants, e.g., air quality maps usually consider hourly or even daily information, there also are many applications where (near) real-time information is critical. For example, in case of hazardous gas leaks, the residents should be warned immediately, and emergency management procedures should also be launched with minimal delay. Enabling real-time access should optimally be resilient to communication failures and thus be able to operate without using a central hub to coordinate all data flows. Edge computing capabilities are critical for enabling decentralized data processing and they can also provide processing support for analyzing the measurements and to identify potentially dangerous situations. Further research is needed to design, evaluate and deploy UAV-edge solutions that can provide the desired access to information.

Massive Sensing: Deploying large amounts of UAVs can offer a comprehensive view of the air pollution levels within a city and help to identify potential issues rapidly. The larger the city, the larger the number of UAVs that need to be deployed with detailed coverage of a metropolitan scale city requiring hundreds or even thousands of UAVs to ensure detailed coverage. Naturally, such coverage would be difficult to provide solely using UAVs, and in practice, the UAVs would complement other sensors deployed in the environment. Nevertheless, even then, this would require fleets with hundreds of UAVs which pose significant logistical challenges for charging, maintaining, and operating them. The maintenance also requires taking a long-term view as components suffer from wear and tear. For example, batteries suffer from capacity loss [178], which means that simply scheduling charging periods is not sufficient but also the health of the battery needs to be monitored over time. Long-term deployments of UAV solutions are needed for a better understanding of factors affecting long-term maintenance and developing mechanisms that can support these operations.

Emission Source Detection: Detecting the source of emissions is a key task for UAV-based pollution monitoring. Current solutions are relatively efficient at optimizing drone flight paths and accounting for meteorological factors, but further research is needed to also integrate interactions with sensors as part of the search process. For example, the accuracy of low-cost sensors is affected by wind, humidity, and temperature and these effects should be considered when determining the area where to direct the search next. The more inputs are integrated into the models, the heavier the processing needs also become and thus there is also a need for further research on developing suitable data processing solutions and architectures that can support emission source detection.

C. Regulatory and Societal Implications

Public Safety, Privacy, and Regulations: As we have discussed, the use of UAVs for air pollution monitoring can raise concerns about public safety and privacy and hence there is a need to regulate the use of UAVs. Current regulations tend to separate the UAV operations and data processing requirements, and it is important to have unified regulatory frameworks that consider both aspects together. Current regulations also are predominantly aimed at aviation safety and securing safety critical infrastructure and separate regulations are needed for the use of UAVs for pollution monitoring—or other uses that are beneficial to society. At the same time, these regulations need to consider potentially dangerous uses of UAVs, including dual-use (i.e., military purposes) and criminal activities.

VIII. Conclusion

UAVs and low-cost air quality sensors that can be integrated with the UAVs are increasingly affordable and available, opening opportunities to harness these technologies to support air quality monitoring. Among others, UAVs can increase the spatial and temporal resolution of air quality data, especially by providing insights into the vertical distribution of pollutants, facilitating searching and detecting sources of emissions, and monitoring and auditing pollution distributions around fixed sites, such as harbors or industrial plants. In this article we have presented a comprehensive survey of the current state-of-the-art in UAV-based air quality monitoring, covering technological challenges in operating, managing, and maintaining drones and the interactions between air quality sensors and UAVs. Based on our survey, we identified research challenges for the future, dividing them into three categories depending on whether they relate to UAV algorithms and techniques, sensor processing pipelines and architectures, or the broader impact and frameworks governing the use of UAVs. While UAVs are already being used in specific air quality monitoring tasks, there is still a long way to go before the full potential of UAV-based monitoring is realized. Our survey takes the first step at setting out this path.

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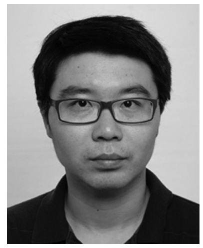

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