AIRWISE
An Airborne Wireless Sensor Network for Ambient Air Pollution Monitoring

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Abstract: Over the last decades with the rapid growth of industrial zones, manufacturing plants and the substantial urbanization, environmental pollution has become a crucial health, environmental and safety concern. In particular, due to the increased emissions of various pollutants caused mainly by human sources, the air pollution problem is elevated in such extent where significant measures need to be taken. Towards the identification and the qualification of that problem, we present in this paper an airborne wireless sensor network system for automated monitoring and measuring of the ambient air pollution. Our proposed system is comprised of a pollution-aware wireless sensor network and unmanned aerial vehicles (UAVs). It is designed for monitoring the pollutants and gases of the ambient air in three-dimensional spaces without the human intervention. In regards to the general architecture of our system, we came up with two schemes and algorithms for an autonomous monitoring of a three-dimensional area of interest. To demonstrate our solution, we deployed the system and we conducted experiments in a real environment measuring air pollutants such as: NH_3, CH_4, CO_2, O_2 along with the temperature, relative humidity and atmospheric pressure. Lastly, we experimentally evaluated and analyzed the two proposed schemes.

1 INTRODUCTION

The atmospheric composition has been continuously changing over the past thousands of years but it is just after the industrial revolution of the 18th century when the atmosphere started to be significantly effected. The huge growth of urbanization and the massive construction of polluting factories and industrial cities, coupled with the lack of legislation and standards for the atmospheric pollutants, led to a progressively increase of the concentrations of dangerous gases in the air. As the atmosphere is essential to support life on our planet, air pollution has long been recognized as a serious threat to human health and to the whole ecosystem. In that context, over the last few decades, governments and NGO's have set rules in the emissions of harmful substances in the atmosphere. Since the early 1970s the EU Air Quality Directive (EUA,) and the U.S National Ambient Air Quality Standards (NAAQS) (Chow et al., 2007) have been working on improving the air quality by controlling those emissions and define maximum atmospheric concentrations.

Due to the hazardous effects of the air pollution to the people and to the environment, air quality evaluation is playing an important role in the assessment of the limits in the exposure of the population and the minimization of health impacts. Human exposure to air pollutants may have serious health effects depending on several factors such as: duration, magnitude and frequency of the exposure. People in their every day life come in contact with various pollutants in the air both indoors and outdoors. As a matter of fact, air quality monitoring is crucial not only for assessing the exposure of the population to the air pollution but it can also be proven extremely useful for scientists in improving the pollution prediction models. In addition it can be used to provide emergency information in the cases of unpredictable disasters. Taking into account the importance of the air pollution monitoring, it is very challenging to monitor how the ambient pollutants are dispersed and diluted in the air both horizontally and vertically. In particular is at high interest a fine grained monitoring in different spatial and temporal distributions.

In relation to the ambient air quality monitoring, several methods and techniques have been developed. Traditionally, the monitoring is done with the use of large monitoring stations placed in static locations such as on top of towers and buildings. However, due

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to their large size and cost of maintenance, these stations are deployed in relatively spatial areas and consequently they can not act as mobile stations. One of the main contributions of our work is the solution towards this problem; the development of a mobile monitoring system for the monitoring of the ambient air pollution.

In this paper we present a WSN system for automated ambient air quality monitoring. Air quality sensors integrated with embedded devices enable the measurement of the air pollution in a very efficient and low-cost way. Our proposing system is able to measure with the use of unmanned aerial vehicles (UAVs) and WSNs and without the need of human intervention, the concentrations of several pollutant, gases and environmental parameters, in three-dimensional environments. We name our system: *AIRWISE*.

The paper is organized as follows: in Section II the related work and motivation is presented. In Section III we propose the theoretical schemes and algorithms as well as the implementation of the *AIRWISE*. In Section IV we present the system development together with our experimental results and their evaluation. Conclusions and future work are presented in Section V.

2 RELATED WORK

The significant advantages in distributed sensor network systems including but not limited to reliability, scalability, dynamicity and efficiency, have brought the WSN systems into the next generation. WSN systems play an inevitable role in our everyday life and they have been widely adopted in sensing and monitoring applications. In (Evangelatos et al., 2013) we have proposed a framework with which we can sense, monitor and control an environment by using WSNs. Apart from the use of WSNs in the area of smart environments, lately they have been used also in the context of air sensing and monitoring. Such a system for example, is described in (Hu et al., 2011), where sensors have been placed on top of cars forming a vehicular WSN dedicated to measure the pollutants' concentrations. In addition, the authors in (Yaacoub et al., 2013) have developed a monitoring system for ground level air quality analysis in Qatar using a WSN. A system using WSN devoted to the monitoring of particular pollutants has been proposed in (Wang et al., 2010), where carbon monoxide (CO) sensors were used for the monitoring of the CO levels in the premises of a university campus area. Other similar systems that have been developed for air quality monitoring using WSN are proposed in (Chen et al., 2013) where the authors have designed a WSN node for remote monitoring of CO and in the (Kavi K. Khedo, 2010) where it is proposed a simulation system for air pollution monitoring using WSNs.

Previous work regarding the air quality and the assessment of health impacts near the airports of UK (Yim et al., 2013) showed that high amounts of pollutants such as CO and NO_x are emitted in the air during the take off and the approach of a plane in an airport. Similar works such as the (Solazzo et al., 2013) and (Lee et al., 2013) are presenting models and estimations on the concentrations and behaviour of the pollutants in the air. In these regards we believe that those models and estimations could be verified and improved with the help of a WSN which would measure those pollutants in real environments. The authors in (Barakeh et al., 2014) are proposing a framework with which they can monitor in real time particulate matter evolution in construction sites in order to assess the air quality, but although such a system can provide a lot of important information on air quality, it is static and bound to the ground.
Due to the recent advancements in robotics, aviation and material sciences, the gap between airborne systems and WSNs has started to be shortened. Drones are being used in a great variety of applications ranging from supporting search and rescue operations (Waharte and Trigoni, 2010) to aerial robotic constructions (Willmann et al., 2012). In addition, with the technological advancements in 3D printing and laser-cutting technologies, it is possible to manufacture low-cost drones with individual features (Nickel et al., 2014). The prior work of (Valente et al., 2011) has used a quadrocopter-drone for implementing a cropping monitoring system in the research field of precision agriculture using WSNs. In (Jude et al., 2007) the authors have developed a WSN composed of bird-sized micro aerial vehicles and ground nodes in which they have analyzed networking performances, such as RSSI behaviour and packet loss rates. Experimental results on the integration of UAVs and WSNs have been presented in (Teh et al., 2008).

Systems and deployments that have been proposed so far are mainly investigating individually, or in the most relevant works two out of the three following domains: air quality monitoring, WSN and UAV. To the best of our knowledge there has not been yet proposed a system that combines WSNs, drones and air pollution monitoring systems. Our work presents a low-cost, automated pollution monitoring system which is comprised of a wireless network with sensors dedicated for measuring the concentration of air pollutants and UAV for performing the measurements in different altitudes, latitudes and longitudes. We came up with two schemes and algorithms resulting in a system's application that can monitor in fine-grained resolution and in near-real time, the ambient air quality in real three-dimensional spaces using WSNs. The information acquired from the system regarding the the pollutants' concentrations in the ambient air could be provided as profitable resource data to air quality scientists for improving their environmental models, to governments as prerequisite information for indexing the air quality of their districts and last but not least as influential dissemination information to the people in order to uphold their environmental awareness.

3 ARCHITECTURE OF AIRWISE

In our paper we present an Airborne WSN system with which we can monitor the ambient air pollution in three-dimensional real space environments. The measurement of the pollutants in the air is being done by pollution sensors which are placed on top of unmanned aerial vehicles (drones). Drones have the ability to fly and hover in the air both manually and automatically. The general design, algorithms and architecture of the *AIRWISE* system is divided in the following two categories: *A.* the theoretical models and *B.* the implementation design. In the following subsections we present, firstly the theoretical models and afterwards the system's implementation design.

3.1 Theoretical Models, Schemes and Algorithms

In our work, in order to deal with the measurement of the three-dimensional air space environment, we propose the following general approach to facilitate exposition: we divide the three-dimensional area we want to investigate (denoted hereinafter as *D*) into "small" equally tessellated cubic-subareas (named as monitor-cubes). The three-dimensional area *D* with its monitor-cubes is depicted in Figure 1. By dividing the whole area of interest *D*, into these monitor-cubes, we are able to distributively monitor the concerned environment and extract individual pollution data for each of them separately. This allows us to create separate "heat" and history pollution maps for each different physical subareas as well as of the whole area *D*. The size of each subarea (monitor-cube) can be defined by the user in accordance with the location and the circumstances of the monitoring area. At the same time, this tessellation gives us the possibility of conducting both fine-grained and macro-scaled measurements. We designate that the measurements in each monitor-cube regarding the pollutants, are taken from their center. Our approach, definitions, schemes and algorithms described below hold for both types of measurements; fine-grained and macro-scaled.

3.1.1 General Definitions

Prior to the description of our approach and models, we need make the following general definitions:

Monitor-Cubes (Subareas $S_{(x,y,z)}$). To facilitate the exposition of our schemes and algorithms, we assume without loss of generality, that the area *D* is cubic. As described above, the three-dimensional area *D* for monitoring the air quality, is tessellated into several "small" cubic subareas *S*, which we denote as: $S_{(x,y,z)}$, where $x \mid x \in [0,k]$ (respectively $y \mid y \in [0,l]$ and $z \mid z \in [0,m]$) and $k+1$ (respectively $y+1$ and $z+1$) is the number of division of the first dimension (respectively of the 2nd and the 3rd) of *D*. The area *D* and its tessellation into the subareas *S* is depicted in Figure 1.

Concentration of Pollutant "a" ($\overrightarrow{CPa}$): There are several pollutants existing in the air such as: Nitrogen Oxides (NO_x), Carbon Oxides (CO_x), Ammonia (NH_4) etc, and their concentrations vary depending on a number of several parameters such as the: location, altitude, temperature etc. We define the vector: *Concentration of Pollutant "a"* ($\overrightarrow{CPa}$) which represents the measured concentration of a pollutant "*a*" in the air. The value of this parameter is obtained by the pollution sensor and its metric is usually in ppm (parts per million). Subsequently, the $\overrightarrow{CPa}$ is normalized between [0,1] in respect to the minimum and maximum concentration values the pollution sensor is able to measure.

Weight ($\overline{W}_{(x,y,z,i)}$). For each subarea $S_{(x,y,z)}$ we define a weight $\overline{W}_{(x,y,z,i)}$ where $i \in \mathbb{N}$. The weight $\overline{W}_{(x,y,z,i)}$ represents the arithmetic mean of the measured concentration of the pollutant $\overrightarrow{CPa}$ in a specific subarea $S_{(x,y,z)}$ of the *iteration (monitoring) cycle i*. The term *iteration cycle* represents one completed monitoring of the whole area *D* and its value *i* represents the i-th *cycle*.

Measuring Rate (MR). As *MR* we define the constant value which represents the measuring rate with which the pollution sensor is collecting pollution data from its nearby environment. The *MR* can be defined as *MR = Samples / Second*.

Duration of Measurement (DM). As the pollutants in the air some times could be burdensome to measure, long time measurements might be required to be collected. Therefore, we define the value: *Duration of*

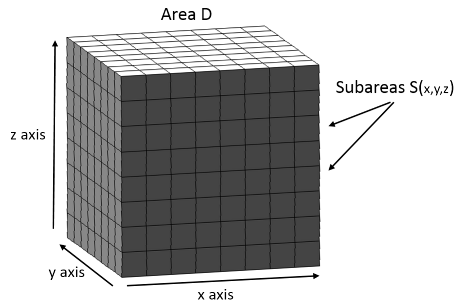

Figure 1: Area D for monitoring and its tessellation to Subareas $S_{(x,y,z)}$.

Measurement (DM), to represent the duration of the measuring process. Depending on the environmental variables of the specific time and location, short time measurements might suffice to collect trustworthy data. However in situations such as toxic or harsh environments, long time measurements might be required to obtain more accurate results.

3.1.2 Schemes

In this section we present two different schemes with which we approach the problem of monitoring the ambient air pollution in 3-D spaces. For each of them we present as well their respective algorithms.

Sequential Monitoring Scheme In the *Sequential Monitoring Scheme*, the routing of the drone and subsequently the collection of the pollution data by the sensors it carries on, are done in a sequential manner. This means that the drone is routed in a static and predefined trajectory whereas the sensors are collecting data systematically from the center of each subarea S. The sensing process and hence the routing pattern starts from the subarea $S_{(0,0,0)}$ and it covers progressively all the subareas until it will arrive to the subearea $S_{(x,y,z)}$. At that point one *iteration cycle (i)* will have been completed. Then the flying and sensing process will restart from the subarea $S_{(0,0,0)}$.

Sequential Monitoring Algorithm (SMA). The pseudo-code of the *Sequential Monitoring Algorithm* (Algorithm 1) representing the *sequential monitoring scheme* is presented below. For each *iteration cycle* and for each subarea, the algorithm measures the concentration of the pollutants and calculates their Weight $\overline{W}$.

Dynamic Monitoring Scheme. In order to use more efficiently the limited and constrained resources of the airborne systems and the WSNs, we propose another monitoring scheme which acts in a dynamic

Algorithm 1: Sequential Monitoring Algorithm (SMA).

Input: Values of: MR, DM, k,l,m
Output: The Weight $\overline{W}_{(x,y,z,i)}$

$MR \leftarrow$ default Measuring Rate
$DM \leftarrow$ default Duration of Measurement
$k,l,m \leftarrow$ size of each axis of area D
$max\_i \leftarrow$ maximum iteration cycles
$x,y,z,i \leftarrow 0$
begin
  while $i < max\_i$ **do**
    for $z \leftarrow 0$ ***to*** $z = m$ **do**
      for $y \leftarrow 0$ ***to*** $y = l$ **do**
        for $x \leftarrow 0$ ***to*** $x = k$ **do**
          $\overrightarrow{CPa} \leftarrow$ Take $MR \cdot DM$ samples of pollutant a
          $\overline{W}_{(x,y,z,i)} \leftarrow$ Arithmetic mean of $\overrightarrow{CPa}$
          $x++$ %next subarea of x axis
        $y++$ %next subarea of y axis
      $z++$ %next subarea of z axis
    $i++$ %next iteration cycle
    $x,y,z \leftarrow 0$ %restart from $S_{(0,0,0)}$
    return $\overline{W}_{(x,y,z,i)}$
end

way. In this scheme the subareas are given a potential of being monitored or not, depending on their previous weight values. We consider a subarea as *stable* when its most recent weights $\overline{W}$ do not alter "much" during a specific time frame. In that case, we can avoid visiting and consecutively avoid monitoring a *stable subarea*. As a result we can use more efficient the limited energy of both the drone and the sensors whilst increasing the time efficiency of the system as well. Lower energy consumption could be translated into monitoring of larger areas and for longer periods.

In order to better describe the *dynamic monitoring scheme*, some further definitions in extension to the general ones (mentioned for the *sequential monitoring scheme*), are needed to be made;

Minimum Iteration Cycles (min_i). The parameter *min_i* is used to define the number of minimum iteration cycles (monitoring cycles) for which the algorithm will keep collecting data from all the subareas, before it will enter into the dynamic mode.

Threshold (Thr). The *Thr*, threshold parameter is an upper bound of the mean accumulated difference between subsequent weights over a specific number of consecutive iteration cycles. Subareas for which their most recent weights are remaining "almost" invariable, are deliberated as *stable subareas*. Moreover, the *Thr* describes the sensitivity of the algorithm. With the term sensitivity we refer to the degree of the pollution variation each subarea is allowed to sustain in order to be considered as *stable*. It is an important parameter, as it allows the adjustment of the tradeoff between the sensitivity of the monitoring process versus the time and the energy needed to complete an iteration cycle i.

Last iteration Cycles to Compare (LiC): The parameter *LiC* delineates the number of the most recent iteration cycles whose $\overline{W}$ will be used in the comparison with the threshold *Thr*.

Idle value ($Idle_{(x,y,z)}$). The $Idle_{(x,y,z)}$ is a parameter which represents the number of iterations for which a subarea remains in *stable mode* and thus is not being monitored.

Maximum Idle state (maxId). The *maxId* bounds the maximum *iteration cycles* for which a subarea is allowed to stay inj *Idle* considered as *stable subarea*. It is used to ensure the reliability of the algorithm in terms of avoiding the formation of holes and to guarantee the refreshness rate of each subarea. It assures that there will not exist any ”ghost-subareas” i.e. areas which might remain unmonitored for a ”long” period of time.

Dynamic Monitoring Algorithm (DMA). In this subsection we present the *dynamic monitoring algorithm* which represents the *dynamic monitoring scheme*. In this algorithm, for each subarea and for each iteration cycle, the concentration and the weights of their pollutants are measured. The same conception holds for the *SMA* with the main difference that the *DMA* takes into consideration the property that a subarea might be monitored or not depending on its stability parameter. Initially the algorithm will monitor the area *D* for a minimum iteration cycles (*min_i*) before it will start taking into account the stability parameter of each subarea. The maximum iteration cycles for which the algorithm will be executed is set by *max_i* and the maximum idle iteration cycles ($Idle_{(x,y,z)}$) for which a subarea can remain at *stable* is set by *maxId*. The *algorithm 2* is presented below.

Algorithm 2: Dynamic Monitoring Algorithm (DMA).

Input: The values:MR, DM, k,l,m, min_i, Thr, LiC, maxId
Output: The Weight $\overline{W}_{(x,y,z,i)}$

$MR \leftarrow$ default Measuring Rate
$DM \leftarrow$ default Duration of Measurement
$k,l,m \leftarrow$ size of each axis of area D
$min\_i \leftarrow$ minimum iteration cycles
$max\_i \leftarrow$ maximum iteration cycles
$Thr \leftarrow$ Threshold defining an subarea as ”stable”
$LiC \leftarrow$ Last iteration Cycles to Compare
$maxId \leftarrow$ Maximum Idle-state value
$x,y,z,i \leftarrow 0$

begin
  while $i < max\_i$ **do**
    for $z \leftarrow 0$ ***to*** $z = m$ **do**
      for $y \leftarrow 0$ ***to*** $y = l$ **do**
        for $x \leftarrow 0$ ***to*** $x = k$ **do**
          if $i > min\_i$ **and** $\sum_{i-LiC}^{i} \frac{|\overline{W}_{(x,y,z,i-1)} - \overline{W}_{(x,y,z,i)}|}{LiC} < Thr$ **and** $Idle_{(x,y,z)} < maxId$ **then**
            $\overline{W}_{(x,y,z,i)} \leftarrow \overline{W}_{(x,y,z,i-1)}$
            $Idle_{(x,y,z)}++$
          else
            $\overrightarrow{CPa} \leftarrow$ Take $MR \cdot DM$ samples of pollutant a
            $\overline{W}_{(x,y,z,i)} \leftarrow$ Arithmetic mean of $\overrightarrow{CPa}$
            $Idle_{(x,y,z)} \leftarrow 0$
          $x++$ %next subarea of x axis
        $y++$ %next subarea of y axis
      $z++$ %next subarea of z axis
    $i++$ %next iteration cycle
    $x,y,z \leftarrow 0$ %restart from $S_{(0,0,0)}$
    return $\overline{W}_{(x,y,z,i)}$
end

3.1.3 Complexity

In this section we present and compare the time complexity of our two proposed algorithms. In the first scheme (*SMA*), the visiting pattern of the subareas by the drone and hence their monitoring by the sensors, is done in a continuous-sequential way, in which all the subareas are monitored in every monitoring cycle. To measure the time complexity of the two algorithms, we consider the number of measurements performed assuming the following: k=l=m=n-1 (in particular the x axis is tessellated in n equal parts and the same holds for the y and z axis); the *transportation time Tt* needed to move from one subarea to a neighboring one in comparison to the *monitoring time* needed to monitor a subarea (*Tm = MR·DM*) is negligible, i.e. Tt<<Tm. Therefore the time complexity of the *SMA* algorithm is: $n^3 \cdot MR \cdot DM$. In the second scheme (*DMS*), the visiting pattern of the drone and the monitoring of the area *D*, is done in a dynamic way based on the decision of whether a subarea is *stable* or not. Considering a subarea as *stable* allows the system to bypass it and move to the next subarea. The efficiency of this algorithm lies in the fact that some subareas might not be monitored which results in less power consumption of the whole system, or in extended monitor space. The time complexity of the *DMA* algorithm is O($n^3 \cdot MR \cdot DM$), but depending

on the algorithm's input values and the environmental parameters the *DMA* could perform even better than that.

3.2 Implementation of *AIRWISE*

As far as the implementation of the *AIRWISE* system is concern, we had to face the following challenges : the limited energy resources of the unmanned aerial vehicles and the sensor nodes; the assembly of a lightweight UAV which would be able to carry on the additional payload of the sensor node; the integration of a flying mechanism that could enable the UAV to fly also autonomously; and lastly the development a WSN system that would be able to support the mobility of the UAV in a three-dimensional environment and transmit its data in near-real time. The implementation and our proposing solution towards those challenges are divided in two subsystems which we present below: the airborne-flying subsystem and the WSN subsystem.

3.2.1 Airborne Subsystem

Due to the nature of the problem of monitoring the ambient air quality, one of the key requirements that we needed to face was the implementation of a system that would be able to take measurements in the air in three-dimensional spaces. The solution that we propose towards this challenge is the use of unmanned aerial vehicles (UAVs) and in particular quadrocopters. Quadrocopters have the ability to take off and land horizontally, they are also able to spin around their vertical axis and most importantly hover in the air. Their ability of hovering in the air allow us to maintain them in the air at specific positions for as long as it is needed. Alternative airborne systems that are using small planes are not able to hover and thus are not suitable for our application. The drone (the term is used interchangeably with the term quadrocopter) that we use in our system is shown in Figure 2 (Left) and we self assembled it from parts which are produced by *3DRobotics*. It is a lightweight and powerful *APM Copter* with a load capacity of approximately 600gr. It benefits from mechanical simplicity and design flexibility and despite its small size it is capable of lifting small payloads. The four blades of the drone as well as its communications are controlled via the *ardupilot*, which is an open source UAV platform able to autonomously control multicopters. We equipped the drone with a GPS antenna and with a telemetry set operating at 433Mhz. In our implementation we used the version of ArduPilotMega 2.6 which gives us a lot of advantages such as: autonomous flight; automatic stabilization; navigation using GPS; reception of telemetry information and control of the drone in real-time using the MAVLink protocol.

3.2.2 WSN Subsystem

To achieve the main goal of our work (i.e. to automatically monitor the ambient air and extract information regarding its quality) we use a wireless sensor network. This network is comprised of two nodes with gas sensing capabilities and one basestation for receiving the data from those nodes. One node was dedicated for the airborne measurements and the other one for ground measurements used for comparisons. Both of them were transmitting their collected data to the basestation. The nodes are comprised of the following components: *a)* an electronic board for accommodating the gas sensors, *b)* the gas sensors, *c)* an external antenna for communicating with the basestation, *d)* a main board with the processor, *e)* a GPS module and *f)* a rechargeable battery. Due to the fact that the nodes and their components are very sensitive and fragile we designed and 3D-printed a cover box to protect them. The complete assembled node, its cover box and the basestation are shown in Figure 2 (Right). Both the nodes and the basestation we used are manufactured by Libellium (lib,). As far as the nodes are concerned, we used as their main board the Waspmote v1.2. The Waspmote node runs with the ATmega 1281 microcontroller at a frequency of 14.7456 MHz and with a memory of 128kB. On top of the mainboard, an 2dBi XBee pro 802.15.4 antenna was integrated for communicating with the basestation. In addition, a sensor board with temperature, humidity, atmospheric pressure and gases sensors was integrated. In particular, the gases sensors that we installed were: Molecular Oxygen (O_2), Ammonia (NH_3), Methane (CH_4) and Carbon Dioxide (CO_2) manufactured by Figaro(fig,). Moreover, we equipped the nodes with a GPS module so that we could time-stamp and position-stamp the measurements taken by the sensors. The energy supply of

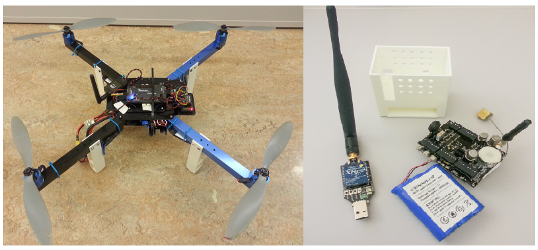

Figure 2: (Left) Drone used in *AIRWISE*, including GPS and telemetry antenna. (Right) Basestation, wireless sensor node and node's cover box.

the nodes was provided by a Li-Ion rechargeable battery with a capacity of 6600mAh. The size of the box including all the components was 8x8x7 cm and it weighted in total 300gr. with a battery weighting 200gr.

On the other endpoint of our WSN subsystem, the basestation was equipped with a 5dBI XBee pro 802.15.4 antenna. It was connected via a USB to a computer for receiving and propagating the information to the *AIRWISE* program, which we developed in C#. This program was designed to be responsible for logging all the information that is receiving, analyze them in order to calculate the concentration of the pollutants $\overrightarrow{CPa}$ and their weights $\overline{W}_{(x,y,z,i)}$ and as well visualize them.

4 EXPERIMENTS AND EVALUATION

4.1 Overall Experimental Set Up

The overall experimental set up of the system can be seen in Figure 2. The weight of the drone itself was: 1.5kg and the additional weight of the sensor node was 0.3kg resulting in a total weight of 1.8kg. For our experiments we chose an area of 6.3 hectares in a heterogeneous environment in-between of a small forestall area and residential buildings.

The experiments we conducted regarding the *AIRWISE* system were divided in the three following categories: a) WSN behaviour, b) Airborne system behaviour and c)integration of the WSN and airborne system.

4.1.1 WSN Experiments

Firstly we run experiments to determine the behaviour of the WSN subsystem. In order to achieve highly accurate calibration of the gas sensors, specific chemical gas tubes need to be used. However, as the measurements of the pollutants with high laboratory accuracy is out of the scope of this paper, the calibration of the gas sensors was done based on trial and error. Nonetheless, even if we could not achieve high accuracy we could obtain very accurate variations in the concentration of the pollutants between different measurements.

For our experiments we installed gas sensors for CO_2, CH_4, NH_3 and O_2, along with sensors for environmental parameters of temperature, humidity and atmospheric pressure. The raw data acquired from the gas sensors, the environmental sensors and the GPS,

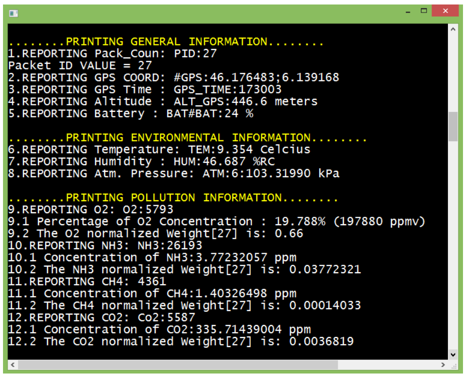

Figure 3: AIRWISE program for receiving, analyzing and visualizing the data collected from the sensor node.

were sent to the basestation using the XBee antenna in four separate packets. Once the packets were received by the basestation, the *AIRWISE* backbone program running on a laptop analyzed the raw data and visualized them in a user friendly way. A screenshot of the program while it was receiving data from the wireless node is shown in Figure 3. In order to complete one data gathering cycle (from the sensors described above) at one specific location, it was required 1 min. and 15 sec. This relatively big amount of time introduced some energy and time related problems that we will discuss below.

4.1.2 Airborne System Experiments

As far as the experiments of the airborne system are concerned, we were able to operate the quadrocopter described previously in two different flying modes: the automatic and the manual one. The automatic flying mode uses the APM 2.6, a GPS receiver, an accelerometer and the "mission planner" software installed on a laptop. Via this software we were able to set specific waypoints in a area and program the drone fly towards those waypoints. Once we set up the waypoints on a graphical interface, we uploaded them to the APM of the drone using the MAVLINK protocol. The benefit of the automatic flying mode enables the drone to take off and land without our intervention. Moreover, we could send commands to the drone,in real time, while it was flying to change its direction. This was proven especially useful when the pollution in some areas was higher than expected. In the second flying mode of the drone i.e. the manual one, we used a Futaba 7-Channel Radio Transmitter. The auto-stabilization system of the APM stabilized the drone even in the presence of strong winds. In order to maintain the safety precautions, the drone was landing when its battery was at 20%. Its maximum flying time with a fully charged 5000mAh 11.1V LiPo battery without any payload, was approximately 15 minutes.

4.1.3 WSN and Airborne System Integration Experiments

In the last set of experiments we combined and tested the integration of the WSN and the drone. For this category of experiments, we defined a fraction of our overall experimental area, a small cubic area *D*. The edges of this cubic area of interest were 39 meters long with a volume of $59319m^3$. This area was tessellated in 3x3x3 subcubes where the centers of each subcube (subarea *S*) were 13 meters apart from each other. Every time the measurements were gathered from each subarea, the collected data were sent to the basestation in near-real time, and simultaneously they were also saved locally. Due to the additional weight of the sensor node and its battery, the maximum flight time of the drone was reduced from 15 to 12 minutes. Initially we set up the sensor node to collect data from all of its sensors (i.e. pollutants, environmental parameters and GPS). In these initial experiments, the time needed to perform measurements from one subarea was 1 min. and 15 sec. and compared to the 12 min. of maximum flight time of the drone, we were able to gather measurements only from 9 subareas. Those 9 subareas correspond to only 0.33 *iteration cycles* and for covering the whole area *D* we needed at least 27 measurements (i.e. one *iteration cycle*). The traveling time from the endpoint of one layer to the starting point of an other was in average 4 seconds.

4.2 Evaluation

In order to evaluate better our algorithms in this real world development, we set the WSN subsystem to measure only the CO_2 in the air, including though GPS and environmental parameters. This shortened significantly the subarea's data gathering cycle to 15 seconds. The experience we acquire from this fact is that for the time being the batteries of the drones, despite being off the shelf, are not yet adequate to perform complex tasks. For this reason we do need to develop efficient mechanisms to overcome those energy constraints.

Figure 4 shows the results we obtained from measuring the CO_2 using the SMA and DMA during the 12 min. lifespan (flying time) of the drone. The *SMA* scheme reported in this lifespan, measurements from 45 subareas. These 45 subareas correspond to 1.67 *iteration cycles*. On the other hand, using the *DMA* scheme (with: *Threshold* at 0.5%, min_i and *LiC* at 5 and the *maxId* at 10), for the same 12 min. life-span, a total of 74 measurements were reported. These 74 measurements correspond to 2.74 *iteration cycles*.

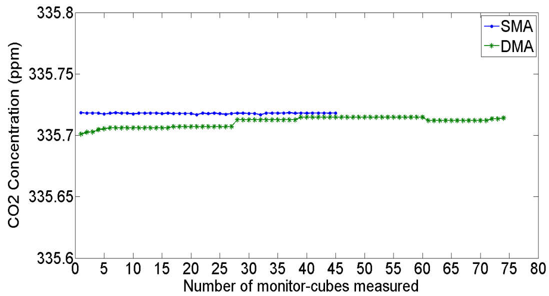

Figure 4: CO_2 reported concentrations using *SMA* and *DMA* algorithms during the lifespan of the drone.

Comparing the performance of the two algorithms, we observe that the *DMA* algorithm performs better and in particular it can report 29 more measurements than the *SMA* with a 0.5% tolerance in the CO_2 concentration. Consequently, the *DMA* is approximately 64% more energy efficient. In Figure 4 we can observe also that the two algorithms report almost identical measurements. The only drawback using the *DMA* scheme is that more messages need to be sent and received which impacts negatively in the energy consumption of the sensor node. Specifically, using the *DMA*, the battery of the sensor was reduced by 4% whereas using the *SMA* it was reduced by 2%. However, comparing the battery depletion rate of the sensor node to the one of the drone, the difference is almost negligible.

Due to the design of the *DMA*, it is let on the freedom of the system operator to decide the tradeoff between the sensitivity of the measurements and their quantity. Meaning that a bigger value in the *Threshold* would allow for more measurements while a smaller value would allow for more precise ones. The advantage of the near-real time monitoring of our system, is that a meteorologist for example in a scenario of a volcanic eruption, could change on-the-fly the trajectory of the drone towards another area of interest. In addition, in emergency pollution situations, by using the architecture of the AIRWISE system, more drones with more sensors could be dispatched for a more detailed monitoring. The *AIRWISE* backbone system which can be run on a laptop, makes the whole system easily portable and transferable.

5 CONCLUSIONS AND FUTURE WORK

In this paper we investigated the challenges of the air quality monitoring and we presented a system-solution using WSNs and UAVs. We proposed a system's architecture together with a theoretical framework and two schemes for monitoring the air pollution in 3D spaces. Furthermore, we showed the implementation of our approach with which the automatic monitoring of the ambient air can be facilitated. We have extended the capabilities of airborne systems by coupling them with WSNs. In particular, we implemented the *AIRWISE* system which is able to monitor pollutants in the air such as: NH_3, CH_4, CO_2, the O_2 percentage and environmental parameters such as temperature, humidity and atmospheric pressure. We developed the system, we run experiments with it and lastly we evaluated and compared our schemes and algorithms in a real deployment scenario.

Our future work plans include scaled up experiments with more drones and sensors acting in a collaborative way. In addition, we plan to investigate the direct interconnectivity between the wireless node and the autopilot system of the drone.

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