Context-Adaptive Multimodal Wireless Sensor Network for Energy-Efficient Gas Monitoring

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***Abstract*— We present a wireless sensor network (WSN) for monitoring indoor air quality, which is crucial for people's comfort, health, and safety because they spend a large percentage of time in indoor environments. A major concern in such networks is energy efficiency because gas sensors are power-hungry, and the sensor node must operate unattended for several years on a battery power supply. A system with aggressive energy management at the sensor level, node level, and network level is presented. The node is designed with very low sleep current consumption (only 8 μA), and it contains a metal oxide semiconductor gas sensor and a pyroelectric infrared (PIR) sensor. Furthermore, the network is multimodal; it exploits information from auxiliary sensors, such as PIR sensors about the presence of people and from the neighbor nodes about gas concentration to modify the behavior of the node and the measuring frequency of the gas concentration. In this way, we reduce the nodes' activity and energy requirements, while simultaneously providing a reliable service. To evaluate our approach and the benefits of the context-aware adaptive sampling, we simulate an application scenario which demonstrates a significant lifetime extension (several years) compared to the continuously-driven gas sensor. In March 2012, we deployed the WSN with 36 nodes in a four-story building and by now the performance has confirmed models and expectations.**

***Index Terms*— Energy management, gas sensor, metal oxide semiconductor, people detection, wireless sensor network.**

I. Introduction

TO IMPROVE people's comfort, health and safety it is very useful to monitor Indoor Air Quality (IAQ). Headaches, nausea, dizziness, eye and throat irritation are usual symptoms of the so-called Sick Building Syndrome (SBS) [1]. Earlier, only CO_2 concentration was controlled, but in the recent several years Volatile Organic Compounds (VOCs) are also used as indicators of persons' comfort. Important sources of VOCs in a building are people (bioeffluents), furniture, building materials, paints, etc. [2]. Another important task in monitoring IAQ is detection of dangerous situations, like pipe leakage (e.g. CH_4 or CO). CH_4 (methane) is a principal constituent of the natural gas, used in almost every household for cooking or heating. When it reaches a certain concentration in air (5–15%), it is flammable and explosive [3]. CO (carbon monoxide) sources are tobacco smoke, gas heaters and stoves, leaking chimneys, etc. It is colorless, odorless and tasteless, hence impossible to notice without a sensing device. In smaller quantities (e.g. 100 ppm) it causes headaches and dizziness after a couple of hours of exposure. Higher concentrations cause headaches and dizziness after 5–10 min, and death within 30 min. Very high concentrations (e.g. 12800 ppm) cause unconsciousness after a couple of breaths, followed by death in less than 3 min [4].

The advantages of Wireless Sensor Networks (WSNs) in IAQ are the flexibility in deployment and savings in time and money by avoiding power wiring and the related infrastructure. On the other hand, if we want to avoid expensive retrofitting to supply sensors from the power grid, battery-powered wireless sensor nodes still consume too much power if the objective is to create a system that should be autonomous and self-sustainable for several years. To prolong the lifetime of the nodes, harvesting units often replenish the power unit [5], [6], providing energy input from the ambient. Nevertheless, energy consumption remains a critical issue and should be managed with great caution. In most WSNs nowadays radio communication (i.e. wireless transceiver) consumes a large amount of energy. There are many energy-efficient protocols developed to reduce its activity [7], [8]. However, in the last years WSNs are used also in applications which require sensors that consume as much (or even more) energy as a wireless transceiver [9], [10]. IAQ monitoring is one of these applications. Gas sensors consume typically 60–70 mW when they are active. Thus, the challenge we face in the system design is the incorporation of power management techniques that schedule both energy-consuming sensors and the wireless transceiver.

An important feature indicating quality of service in WSNs is coverage [11]. We address it by pre-deployment modeling of the monitored area (building), taking into account airflows, window and door position, etc. It is useful to define the initial values of the system variables, and critical times and concentration values. Coupled with the information extracted from the sensors (the PIR sensor and the gas sensor itself), the

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system is able to predict the behavior and the diffusion of a gas leakage and to adjust the frequency of the measurements to promptly send alarm messages if necessary. Also, actuators in a form of ventilation control can be included to the WSN as grid-powered nodes. To show the advantages of our proposed approach in terms of network longevity and reliability of battery-operated node, we perform simulations and power consumption assessments for two typical monitoring scenarios:

1) analysis of the gas concentration due to contamination produced by a person during longer periods;
2) detection and analysis of contamination due to a dangerous event like a pipe failure.

In this paper we present a study of a flexible, context-aware WSN for smart gas monitoring. The contribution to energy consumption reduction, to ensure several years long battery lifetime, is at three levels:

1) at **sensor level** we exploit: a) pulse mode operation for measuring gas concentration from the MOX gas sensor and b) early detection of safe concentration conditions;
2) at **node level** we achieve low power consumption by managing the sleep state and the duty-cycled activity of the node based on the detection of people presence in the ambient;
3) at **network level** we enhance the power saving of each single node and we increment the lifetime of the whole network by exploiting the information received from the neighbor nodes.

To the best of our knowledge, it is the first study of that kind in smart gas monitoring systems, combining knowledge from lower levels (sensors) up to the network level exploiting multimodality of the network (by adding the people presence sensing). In addition, our predicted node lifetime is much bigger (almost 3 years) than the biggest predicted lifetime in literature (113 days in [12]). Our deployed testbed has already exceeded 3 months by the time of writing this paper.

The remainder of the paper is organized as follows. Section II surveys the related work in MOX gas sensors and WSNs for gas monitoring. Section III gives an overview of the network we designed and Section IV the characterization of the network regarding energy consumption reduction. Section V presents several case studies with simulations that show the benefits of the proposed system, as well as the testbed environment. The conclusions and future work plans are brought in Section VI.

II. Related Work

When designing an energy-efficient system for battery-powered applications, a multidisciplinary approach is necessary. In particular the expertise from WSNs design and the knowledge of MOX gas sensors and their characterization are crucial to achieve the maximum power saving at the same quality of service. In this section we present the state-of-the-art in those two fields, since to the best of our knowledge, nobody has addressed a holistic approach under power management perspective. Indeed, one of the main contributions of this paper is a multi-level power reduction by coupling knowledge from hardware layer and sensor design to upper levels with network management and system optimization. In our opinion, that is a crucial task for implementing a functional autonomous long-lived WSN for smart gas monitoring.

TABLE I
Comparison of Gas Sensor Technologies

Gas sensor technology	Gas detection process
Pellistor	Energy liberated changes by burning a combustible gas
Infrared	Change in detector signal between the infrared source and infrared detectors
Electrochemical	Chemical reaction produces a current directly proportional to the concentration of gas present
Surface Acoustic Wave (SAW)	The mass change of the gas sensitive membrane causes frequency change
Quartz microbalance (QMB)	The mass change of the quartz crystal changes the resonant frequency
Metal Oxide Semiconductor (MOX)	Resistance change of the sensing layer.

A. Design and Characterization of MOX Gas Sensors

There are several different technologies used for gas sensor manufacturing, divided in various groups [13]–[15]. A short overview of the nowadays commercially available ones (according to [16]–[18]) is given in Table I. Due to advantages over other technologies, like the small form factor, fast response time and lower energy consumption, electrochemical and MOX technology are the ones most considered for WSN applications. Electrochemical sensors show linearity for the concentrations we are interested in, but have life expectancy of only 1–2 years. Sensors with maximum 5 years lifetime must work under controlled environment (i.e. controlled humidity and temperature not to degrade the electrochemical film) and are 5 times more expensive than MOX devices of equivalent accuracy which are much more robust to ambient variations. In addition, to the best of our knowledge, the electrochemical sensors for the gases monitored for IAQ that we are interested in are not commercially available. On the other hand, solid state sensors can detect most chemicals in Lower Explosive Limit (LEL) ranges and have life expectancy of 10 years or more [19]–[21]. These are the reasons we decided to develop our system with MOX gas sensors.

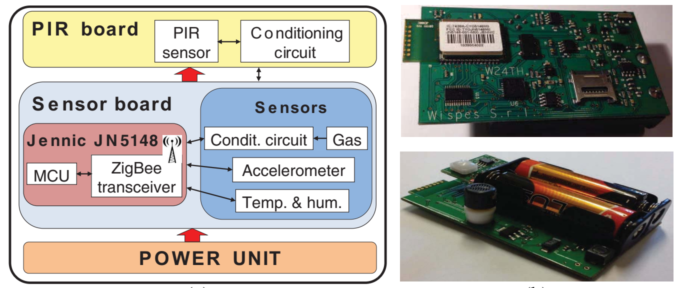
In [22], it is shown how the sensitivity, selectivity and response time of MOX gas sensors strongly depend on the sensing layer temperature. A detailed study of the pulse mode for three different fabricated MOX gas sensors is presented in [23]. The sensors they fabricated and presented in these two papers consume only about 9 mW, which is the power saving of an order of magnitude compared with typical commercial off-the-shelf (COTS) MOX gas sensors. In [24], authors study dynamic behavior of low-power CO MOX sensors (COTS sensors from Figaro) operated with pulsed temperature profiles and conclude that sensor thermal dynamics changes as a function of the CO concentration. They propose two parameters describing the sensor response shape, to provide an indication of the gas concentration, regardless of any calibration.

These papers show the intensive effort to reduce the power consumption of the MOX gas sensors with pulse operational mode. Upon the state-of-the-art and expectations of further COTS gas sensors power consumption reduction, we decided to develop our system with MOX technology gas sensors. We explore the possibility of determining the presence of contaminant from the transient gas sensor behavior, which shortens the time that the gas sensor has to be heated and reduces its energy consumption.

B. WSNs for Gas Monitoring

There are several examples in literature of sensor systems for monitoring IAQ. In [25], an automated decentralized indoor climate control system is presented, including stationary wired multi-gas sensor modules and wearable wireless devices. Energy consumption of the system is not mentioned. Postolache *et al.* [26] present a WiFi network for indoor and outdoor air quality monitoring with MOX sensor arrays from Figaro [18]. They are focused on advanced onboard processing and data publishing on the Web. Power consumption of the nodes is very high (8 W). Choi *et al.* [27] and Rossi [28] present design and implementation of sensor systems for air pollution monitoring with IEEE 802.15.4/ZigBee communication protocol. Both mounted various types of gas sensors on their boards, developed an automated sensor-specific power management system and used pulse mode of the gas sensors, but the average current consumption of their solutions is still quite high (about 100 mA). Gupta *et al.* [29] propose an adaptive sampling algorithm for wireless air pollution sensor network. The performance evaluation of the algorithm was carried out in MATLAB using real CO datasets acquired by commercial ICOM monitors, but the algorithm has not been implemented on the node. De Vito *et al.* [12] present a WSN of nodes with electronic noses, based on TelosB platform that in sleep state consumes 12 μA. They introduce an on-board sensor fusion in the form of a feedforward neural network providing local estimation of chemicals concentrations based on which decision is made whether to send the message through the network or not. They measured the power consumption of the node and predict 113 days of battery lifetime in case of 1% probability of high gas concentration (i.e. need for transmitting).

We focus on the power consumption reduction of the gas monitoring WSN through design of an ultra-low-power node. The power consumption of our node in sleep state is only 24 μW (8 μA @ 3 V). Instead of on-board computation and estimation of gas concentration, we propose a multimodal network that reduces the activity of the sensors (reducing the energy consumption) without jeopardizing safety. Information about presence of people and the messages received from the other nodes in the network enable context-aware adaptation of the gas sensor sampling rate. That feature is essential for achieving average power consumption of the network low enough to survive at least for one year on a battery power supply, without losing important information from the environment at the same time.



(a) (b)

Fig. 1. Sensor node used for gas monitoring. (a) Block architecture. (b) Top side and bottom side.

III. Network Architecture

The network we propose consists of several sensor nodes organized as IEEE 802.15.4/ZigBee network, cluster-tree configuration. The main node is the ZigBee coordinator, and the end devices are connected to the routers in a star-like manner. The coordinator and the routers are mains powered and their energy consumption is not an issue. On the other hand, end devices are battery-powered and it is crucial to reduce their energy consumption in order to prolong the network lifetime. All the nodes have the same hardware architecture, and differ only in the software application. In order to reduce the power consumption of the hardware as much as possible, we designed a wireless sensor node with the possibility of controlling very precisely the activity of its components.

A. Sensor Node

The architectural diagram and pictures of the sensor node we designed are shown in Fig. 1. The node is built around Jennic JN5148 module, placed on the sensor board, together with several sensors connected to it. The PIR board is connected to the sensor board over GPIO pins to provide the information about the people presence. The power unit contains two AA batteries, but can be also augmented with a power harvester.

1) Node Platform: The core of the sensor node is the Jennic JN5148 module [30] which is an ultra-low-power, high performance wireless microcontroller targeted at ZigBee PRO networking applications. The device features an enhanced 32-bit RISC processor, a 2.4 GHz IEEE 802.15.4 compliant transceiver, 128 kB of ROM, 128 kB of RAM and a rich mix of analogue and digital peripherals. Compared to other similar platforms (e.g. TelosB [31]), it gives about 35% power savings—its power consumption is 15 mA for TX and 18 mA for RX. Using ZigBee PRO protocol stack enables us to form a standardized and easy-expandable network. The board is equipped with several additional sensors—an accelerometer, a temperature and humidity sensor and a gas sensor with its conditioning circuit—useful for various ambient monitoring applications. Here we focus on the gas sensor and its conditioning circuit. A microSD card reader, intended for local back-up, data logging and firmware update, is also present on the node.

2) Gas Sensor: The advantages of the MOX sensors (small form factor and power efficiency), as well as the

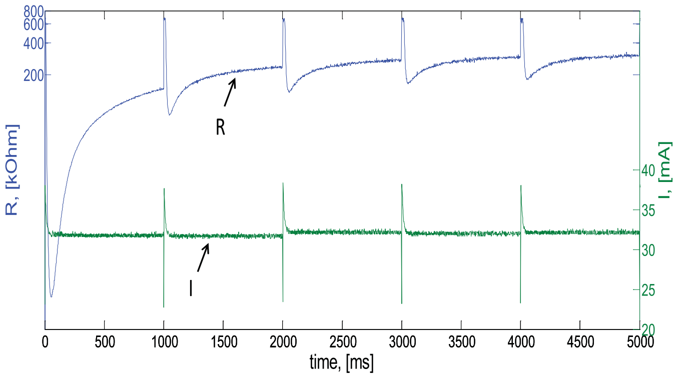


Fig. 2. Output of the gas sensor conditioning circuit—resistance of the sensor and current consumption of the heater. Time of heating: 1 s. Sleep time: 5 s (not depicted).

effort that has been done in microelectronics for production of MOX sensors (reducing power consumption, increasing selectivity and sensitivity), described in Section II-A justify their usage in WSNs. Disadvantages of this type of sensors (sensitivity to temperature, humidity and airflow) have to be taken into account by design and deployment of the nodes.

We used a commercially available sensor MiCS-5121 from e2v technologies [17]. It is a sensor that detects VOC (including CH_4) and CO. We built a flexible conditioning circuit for the gas sensor that enables us to control the heater voltage by a DAC from the MCU and monitor the sensor resistance and current consumption on the ADCs. By modifying the heater voltage, we can control the temperature of the heater, which is responsible for the chemical reaction progress. Fig. 2 shows the resistance of the gas sensor and the current consumption of the heater when a pulsed regime is applied to the sensor, with 1 s heating the sensor and 5 s sleep. The sleep time, during which the sensor resistance significantly increases, is not shown at the plot for visual clarity. It is important to note two different transient behaviors—first one after the sensor has been idle for a long time (a day) and the others when the sensor has been idle for 5 s. That transient behaviors will be discussed in more details later. The temperature has a significant effect on sensor sensitivity (e.g. at a lower temperature the sensor is more sensitive to CO). However, this is a commercial sensor and its calibration and accuracy assessment is performed and certified by the vendor, and it is out of the scope of this work.

B. PIR Module

The Pyroelectric InfraRed (PIR) sensor is a low-power, low-cost sensor that detects person presence by detecting variations of incident infrared radiation of a body that is not in thermal equilibrium with the environment. It is often used in alarm systems providing a simple digital presence/absence signal. Being passive and very low-power, but still reliable, it is very convenient for usage in battery-powered systems, often as a trigger for energy-consuming video cameras [32]. From our experience [33], [34], PIR sensors, although very low-resolution, are able to give useful information when densely deployed and cooperating. Another advantage is that they have almost no impact on people's privacy. We designed a separate board with Murata IRA E710 PIR sensor and a conditioning circuit able to modify the sensitivity (range) of the PIR sensor, with two outputs: a digital and an analog output. Digital output wakes the node up from the inactive state on a detection of a person movement in the monitored area. From the analog output we can recognize the direction of the movement of the person [35], which can can be used for adjusting the frequency of gas concentration sampling according to the number of people in the room. In this work we show the advantages in terms of energy-efficiency and quality of service if we merge the information about the gas presence from the gas sensor and information about the people presence from the PIR sensor. Although the PIR module introduces a non-negligible power consumption to the node, we will later show that additional power consumption is justified by significant savings introduced with adaptive sampling rate.

IV. Power Saving Techniques

A. Sensor Level

1) Pulse Mode Reading: To detect the gas, the MOX sensor has to be heated (76 mW required to reach the 340 °C operating temperature [17]). If the sensor is used in a continuous mode, energy consumption would be too high and the node, battery-powered, would run out of energy in a couple of days. By keeping the node in sleep state and waking it up periodically or on an event, we can reduce the energy consumption. With putting the JN5148 in sleep state and turning off all other components on the sensor board, we accomplished an ultra low current consumption of 8 μA at 3 V, which is a pre-requisite for designing a long-lived WSN. In order to ensure prompt reaction to gas concentration increment, the inactive time of the gas sensor has to be low enough. Thus both duty cycle and active time of the sensor should be low, to provide low energy consumption and appropriate quality of service. Hereafter we present the challenges of that task. Duty cycle (D) of the node activity is defined as the fraction of time when the node is *on*

$$D = \frac{t_{on}}{T}; \quad T = t_{on} + t_{off}. \tag{1}$$

Power consumption of the node depends on the duty cycle

$$P_{avg} = \frac{P_{on} \cdot t_{on} + P_{off} \cdot t_{off}}{T}. \tag{2}$$

Since power in inactive state (P_{off}) is usually several orders of magnitude lower than the power in active state, and also in our case it is, we can approximate the average power consumption as

$$P_{avg} = P_{on} \cdot D. \tag{3}$$

Hence, to decrease the node power consumption, we want to reduce its duty cycle (D).

When duty-cycling, the node wakes up periodically, turning on its gas sensor and its radio. While the node is in sleep, it can't detect any gas concentration, neither can receive any message on the radio. If the event (i.e. dangerous gas concentration or message reception) occurs just after the node switches to sleep mode, the node reacts after t_{off}, which is the

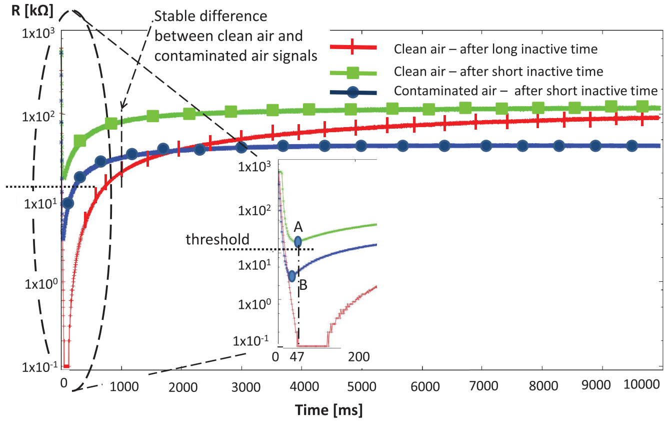


Fig. 3. Resistance of the gas sensor when turning on the heater.

worst case reaction time. To reduce the duty cycle, we should decrease the t_{on} time and increase the period (T) as much as possible, taking into account some application constraints such as the reaction time of the whole system to hazardous events. t_{on} minimum value is limited by the gas sensor technology. In this paper we will show the benefits of a conservative sampling rate and we set t_{on} fixed to 1 s. Further on we will use sampling rate of the gas sensor ($1/T$) as the key variable of the system, instead of the duty cycle.

Fig. 3 shows 10 seconds of the gas sensor output measured for three cases: turning the heater on in 'clean' air after a long period of inactivity and after a short period of inactivity, as well as turning the heater on after a short period of time in contaminated air. We see that the MOX sensor has a peculiar behavior when used for the first time after inactivity interval of about 1 hour or more. Its resistance falls to a very low value and then it slowly reaches the steady state which provides faithful reading of gas concentration. This process takes about $10s$ and it is a consequence of impurities that got deposited on the sensor surface during long off-period. After burning the impurities, the resistance is slowly getting back to the steady state. This is a slow process, which affects the initial reading of the sensor. On the contrary, when turning the sensor on after a shorter period of time, that initial degradation of resistance is smaller because not that many impurities have been caught on the sensor surface. It provides, after a short negative peak, a reading which is not fully static, but already very informative about the gas concentration. In fact, if we compare the two curves corresponding to clean and contaminated air (i.e. green and blue curves in Fig. 3 respectively), we notice that their distance does not change much after approximatively 1 second.

These observations lead to the following conclusions: if we never let the sensor sleep for a very long time (i.e. hours) we can use its reading after a relatively short time (i.e. 1 s) to assess air contamination. On the contrary, if we let the inactivity period grow too much, we necessarily have to wait for about 10 s to get a reliable measurement from the sensor. Of course, the inactivity interval, which determines the deposition of impurities, depends on the environment where the sensors are used and on the air pollutants. In our testbed, we noticed that approximately an hour of OFF state is necessary to pollute the sensor surface and to force a 'long' waiting for the next measurement. From these considerations we can define constraints on duty-cycling strategy for the MOX gas sensor used by the system. Its t_{on} time can be around $1s$ only if its t_{off} time is constrained to be significantly smaller than 1 hour. For the specific sensor we experimented that 20 min is a safe maximum threshold on inactive time to avoid the undesirable long transient in active state and this sets a duty cycle D of 0.085%.

2) Early Detection of Safe Conditions: We also observe that we could reduce the active time even more aggressively by measuring the value of the negative peaks during the initial transients after a short t_{off}. In fact, our preliminary observations show that these peaks correlate quite well with gas concentration. With this approach the microcontroller can threshold resistance between A and B (Fig. 3) to find out at the beginning of the heating (after only a couple of tens of milliseconds) if there is a high concentration of the contaminant gas in the air. Thus, if the microcontroller detects the resistance corresponding only to the sensor surface impurities in the 'clean' air, we can turn off the sensor and save power. For example, in Fig. 3 the microcontroller can understand after 47 ms that the air is clean. Thus, an adaptive method to determine the minimal pulse duration could have the benefit to strongly reduce the power consumption of gas sensor in situations with clean air—in this test the power consumption is only about 47 $ms \times 76\ mW = 3.5\ mJ$—compared to hundreds of mJ needed for a 1–5 seconds t_{on}. However, this approach can only be used to detect safe condition of the environment (which are usually the most frequent occurrences) and cannot assess values of the gas concentration. For more accurate information about the contaminant presence and concentration, we still need to activate the sensors for at least t_{on}. This kind of power saving technique is in an early stage of consolidation and further experimental evidence must be collected within future work to verify this hypothesis.

B. Node Level

1) Multimodal Concept: To maintain both safety and comfort, and to reduce the energy consumption of the system, we can modify the frequency of gas sensing (i.e. $1/T$) according to additional information and triggers which make the node aware of the current context in the environment. For instance, the awareness about the presence of people is useful, because the node can decrement the rate of the measurements in case of no occupancy of the ambient, and still guarantee a sampling frequency suitable to detect possible contamination. In this case, the presence of people is detected by the PIR sensor. A cost function like (4), in form of a set of rules or a look-up table, ensures both the desired quality of service in case of occupancy and the minimum level of safety in case of contamination

$$\frac{1}{T} = f(P, d, v). \tag{4}$$

In definition of the function, P is people presence detected by the PIR sensor, d position of a person in the house, and v velocity of gas diffusion.

According to that, the proposed system is able to monitor IAQ in various situations. We can divide those situations into two groups: quasi-stationary detection and event detection.

2) Quasi-Stationary Detection: VOC concentration highly depends on the person presence (not only by physiology, but also by using cleaning products, cooking, smoking, etc.) and during time in a room (without proper ventilation) we can notice continuous gas increment. Thus, it is useful to merge data extracted from the people presence detector to develop a flexible, energy-efficient system that enhances comfort of people in the room regarding air quality. Thanks to the PIR sensor we can detect how long somebody is in a room and dynamically modify the frequency of gas concentration sensing. If there are people in the room for a long time, it is expected that the contamination of the air rises faster. Thus, the node increases the gas sampling rate.

3) Event Detection: Detecting dangerous events like high gas concentrations is important for people (and infrastructure) health and safety. In order to detect dangerous events, we notice the importance of model-based sampling rate calibration. Pipe failure is the most common source of dangerous gas concentrations indoor. Before deploying the network, it is necessary to obtain information about the pipe placements in the building, to know which rooms are connected with pipes and which nodes have to be woken up first in case of leakage in a certain room. Also, history of previous failures and state of the pipe infrastructure have to be investigated in order to designate each room a leakage risk factor. Modeling the pipe failures before network deployment can help us decide about nodes' placement in the room and their sampling rates (including activity of the radio and activity of the gas sensor). The inactive (sleep) state is critical in terms of reaction time. Modeled gas flow rate is important for determining the maximal reaction time of the node, that has to be shorter than the time of a gas to reach the dangerous (flammable/explosive/lethal) concentration. Also, for the rooms where initial field tests and models show low risk of dangerous gas concentration, we can capture the gas sensor value only on detection of a person presence by the PIR sensor.

When a node detects gas concentration higher than a predefined threshold, it sends an alarm message to other nodes, triggers the control system to start a proper reaction to the situation and increases its sampling rate to ensure more precise monitoring of the gas concentration. Also, when the gas concentration is low and there are no other warnings of a possible enhanced contamination, the node decreases the sampling rate. After detecting dangerous gas concentration values, safety becomes more important than the network lifetime. Hence, we wake the node up to continuously sample the gas sensor and inform all the nodes in the network (building) to do the same thing, which enables tracking of the gas flow, that is useful for post-leakage analysis and reparation of the building. For that case, it is very important to ensure a proper radio duty cycle, i.e. reduce reaction times.

TABLE II
SENSOR NODE CURRENT CONSUMPTION AT 3 V

(a) SENSOR BOARD

State			Current Consumption [mA]
MCU	Radio	Gas Sensor	
sleep	off	off	$8 \cdot 10^{-3}$
on	on, idle	on	55.80
on	on, TX	on	58.02
on	off	on	38.06
on	off	off	8.08
on	on, idle	off	21.80
on	on, RX	off	9.62

(b) PIR BOARD

State	Current Consumption [mA]
no event	0.051
event	0.210

C. Network Level

To further increase the energy savings, we can use *multimodality* and increase cooperation in a distributed WSN by coupling with the information about gas concentration from the neighbor nodes. For instance, if the PIR sensor detects a person in a room (e.g. living room), the node can postpone the increment in sampling rate if it doesn't receive the alarm message from the node in the critical room (e.g. kitchen). As we will show later in Fig. 7, CO gas takes about 15 min to diffuse in the living room and reach the concentration of the kitchen. According to that, the node in the living room does not have to immediately increase the gas sampling frequency upon detecting a person in the room, but it can wait for the time needed by the gas to spread. It has impact to the whole network, but the algorithm is local to each node and can be embedded in the cost function already discussed. In particular, eq. 4 can be extended as following:

$$\frac{1}{T} = f(P, M, d, v) \tag{5}$$

where M is the alarm message received from a neighbor node.

V. EXPERIMENTAL RESULTS

A. Node Characterization

Table II shows the sensor node current consumptions for different states of its components, with 3 V power supply. We can notice that the PIR board introduces another 51 μA to the sensor board, which significantly increases the 8 μA sensor board sleep current consumption. Nevertheless, we will show that power increment is justified—using information from the PIR about presence of people we adaptively reduce activity of the node and thus reduce total energy consumption of the node and maintain high quality of service. The energy consumption of a node can be modeled with a behavioral flowchart. A behavioral flowchart consists of all power states that a node is going through its lifetime and the transitions between them. For each state and each transition we need to know the power consumption (P_{state}, P_{trans}) and time (t_{state}, t_{trans})

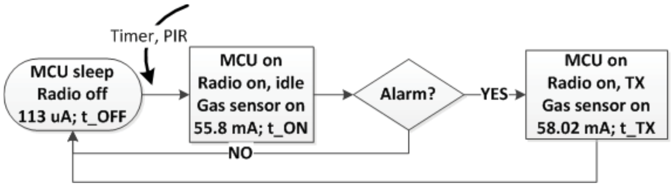


Fig. 4. Behavioral flowchart of a periodically awakened sensor node, with gas sensor in pulse mode.

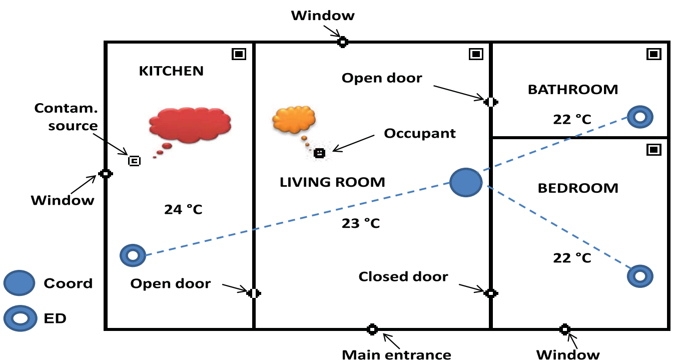


Fig. 5. Smart gas sensor network deployment used in CONTAM simulations.

the node spends in [36]. The energy consumption of the node can then be calculated as the sum of energies in all states and energies of all transitions between states:

$$E_{node} = \sum_{state} P_{state} \cdot t_{state} + \sum_{trans} P_{trans} \cdot t_{trans}. \quad (6)$$

Behavioral flowchart of the designed node for smart gas monitoring is shown in Fig. 4. We measured the power and times for every power state and transitions between them. For the sake of visual clarity, not all information is depicted. The information from the PIR sensor (about the presence of people) and from the transceiver (about the reception of an alarm message from another node in the network) can be used to modify the sampling rate and adjust the sensor to the situation, with effort of minimizing the node activity without decreasing the quality of service.

B. Simulation Results

To design a safe gas monitoring system and to show the benefits of our approach based on adaptive sampling rate in terms of good quality of service (i.e. safe reaction time), we simulate gas diffusion in CONTAM, one of most popular free multizone simulation tools [37]. The simulated gas flow diffusion permits to choose the set of sampling rates used by the system accordingly to the number of people present in the room, that we will profoundly discuss in next subsection. For creating some everyday life case studies of air pollution, we use a simple testbed, a typical house (4 zones—living room, kitchen, bedroom, bathroom), with a dangerous contamination source in one room (kitchen) and one person living in the house. The house and the smart gas detection WSN deployment is depicted in Fig. 5.

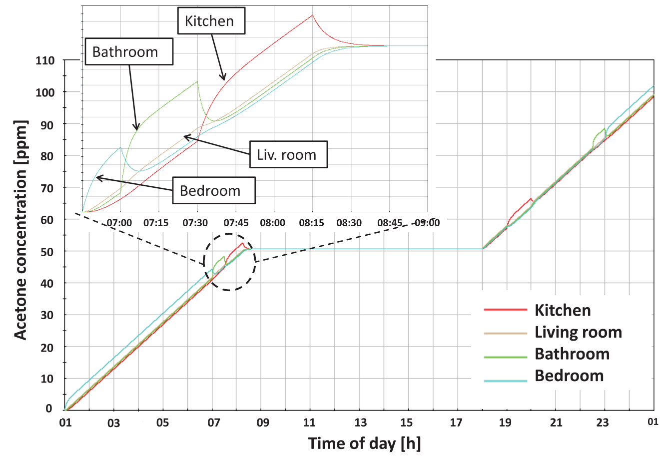


Fig. 6. Acetone (VOC) concentration in the house from Fig. 5 during a typical day.

Fig. 7. CO concentration in the house from Fig. 5 during 1-h-long pipe failure.

1) Everyday Life: Occupants are continuously changing VOC concentration in the house during a typical day. Here we show simulation results of a constant gas flow (without ventilation) in a typical house shown in Fig. 5. For the simulations we consider the following occupant presence:

1) 07:00–07:30 — bathroom
2) 07:30–08:15 — kitchen
3) 08:15–18:00 — outside the house
4) 18:00–19:00 — living room
5) 19:00–20:00 — kitchen
6) 20:00–22:30 — living room
7) 22:30–23:00 — bathroom
8) 23:00–07:00 — bedroom.

Fig. 6 shows the acetone (one of VOC gases) concentration distribution in ppm for each room in the house (all doors open) during the day. We approximate the acetone contamination produced by a person to be constantly 1 mg/s. We notice in the enlarged part of the image (showing the period 7:00–9:00) how the acetone concentration is changing in different rooms of the house depending on how the person is moving—from the bedroom, to the bathroom, then to the kitchen, and then leaving the house at 8:15.

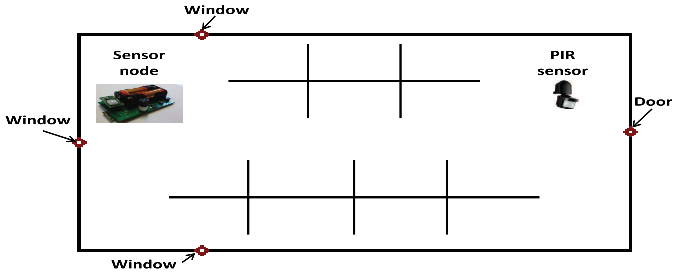


Fig. 8. Model of the open office used to assess the system autonomy.

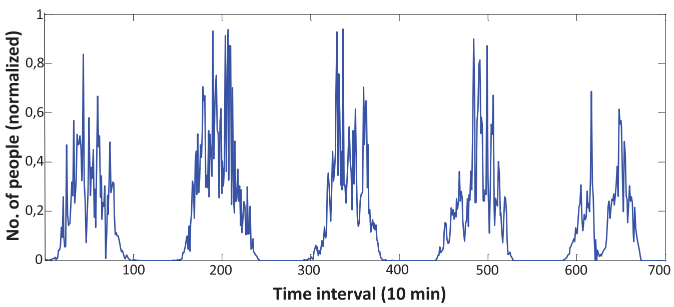


Fig. 9. Number of people in our laboratory (open office type) detected by the PIR sensor during five days.

2) Gas Pipe Failure: Fig. 7 shows gas concentration in the house from Fig. 5 during a hazardous event, 1 h long pipe failure in the kitchen (13:00–14:00). It produces a constant leakage of CO with 500 mg/s rate. Figure shows how fast the gas is spreading through the house. It takes about 15 min for the gas concentration in the living room and the bathroom to reach the same value of the concentration in the kitchen. The CO concentration in the bedroom remains zero, because the simulation was performed with setting the closed door.

C. Autonomy of the System

The gas flow rates simulated in CONTAM suggests to determine the gas sensor sampling rates and to estimate the network lifetime in MATLAB, using measured power consumptions of the node (Table II) and expression (6). To show the advantages of adaptive sampling rate and multimodality introduced at node and network levels, we simulated several modes of monitoring air quality using the same WSN deployed in the ambient.

a) Gas sensor in continuous mode.
b) Fixed sampling rate ({100; 50; 20; 10; 5; 1; 0.1} $\times 10^{-3}$ Hz).
c) Adaptive sampling rate (combination of {20, 10, 5 and 1} $\times\ 10^{-3}$ Hz sampling rates) with occasionally waking up the node and the transceiver during the node (and gas sensor) inactive time. The algorithm will be presented later and is based on information about the environment received both from PIR sensors and other nodes.

To assess the proposed power saving techniques and to compare the best trade-off between sampling rate, system reaction time and sensor nodes lifetime, we use a wide environment such as an open office in a building (Fig. 8). Since the structure

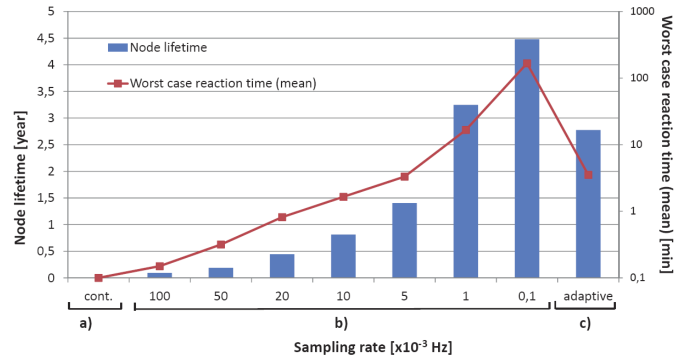


Fig. 10. Node lifetime and the mean worst case reaction time for different sampling rates, with $t_{\mathrm{on}} = 1$ s.

of our lab corresponds to the open office type from Fig. 8, we mounted there a PIR sensor and captured events for 5 days. Fig. 9 depicts the normalized number of people detected by the PIR sensor. Using Mode *c*), the sampling rate is being adapted based on the information about number of people (the more people or passages are detected in the office, the higher is the sampling rate and *vice versa*). In particular, using that information from the PIR sensor, we suppose the following:

1) during working hours (from 8–20 h) we have $10\ \times 10^{-3}$ Hz sampling rate by default;
2) the peaks of presence in the office are detected in the intervals 10:00–11:00 and 15:00–16:00. In these intervals the nodes set 20×10^{-3} Hz (very frequent gas sampling—lots of people present, e.g. a meeting);
3) during the night there are usually no people in the office, but for safety and air quality reasons we can suppose that in average we have for 10 h 5×10^{-3} Hz sampling rate and for 2 h 1×10^{-3} Hz sampling rate.

Fig. 10 depicts the mean worst case reaction time and the node lifetime for different sampling rates of the sensor with $t_{on} = 1\ s$, for the cases specified in section IV-C. The node is equipped with two AA batteries providing 3 V and 3000 mAh. For the continuous mode the reaction time is zero (thus only illustrated in logarithmic scale). Fixed sampling rates have a constant worst case reaction time. For adaptive sampling rates, we calculate the mean value of the worst case reaction times of the sampling rates that are combined.

The benefits of duty-cycling the node activity in terms of lifetime prolongation are evident. A node with a continuous gas sensing would survive only for 2 days and 6 hours. A 0.1×10^{-3} Hz sampling rate, on the other hand, provides very good node lifetime (4.47 years). The lifetime of the node using the adaptive sampling rate is 2.77 years, as showed in Fig. 10 (Mode c) adaptive sampling rate) which is much less than the 4.47 years achieved using fixed rate. However, simulation results show that we are facing an *inactive time – node lifetime* trade-off. The reaction time, intended as the worst case interval time between the event of dangerous concentration and its detection, is unacceptable in case of 0.01% activity rate. As depicted, the reaction time is 167 min with the risk of missing important events. If a system designer

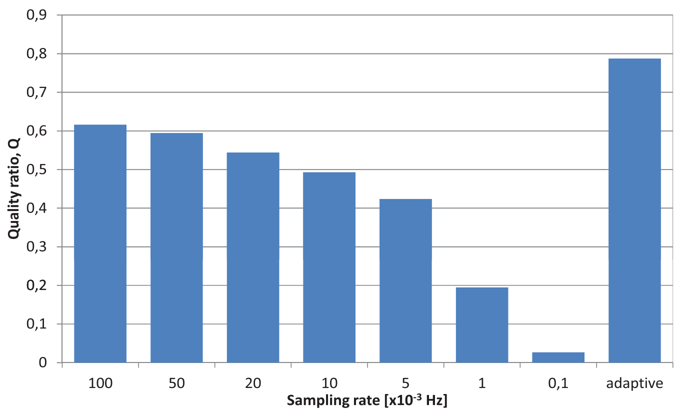


Fig. 11. Quality ratio (node lifetime/worst case reaction time) for various sampling rates.

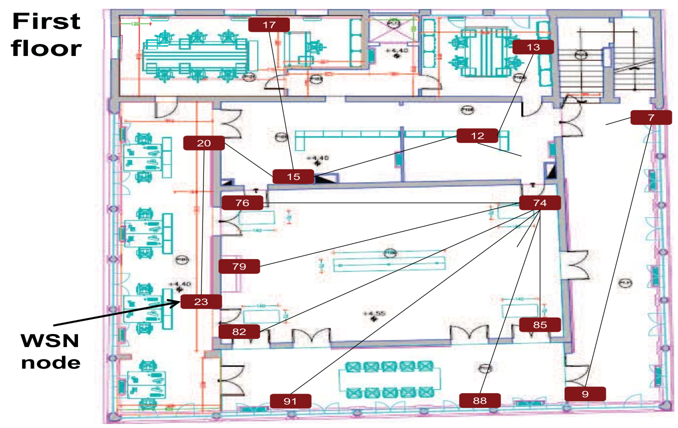


Fig. 12. First floor of the deployed WSN with 36 nodes—Palazzina della Viola, Bologna.

wishes to accomplish at least one year of system autonomy (a typical demand for a real-life application) using a fixed rate of 5×10^{-3} Hz appears a good trade-off between autonomy and reaction time. Anyway, with adaptive sampling rate, the results are even better since it achieves both long node lifetime and low reaction time.

Indeed, we define the following quality ratio as a metric:

$$Q = \frac{L}{t_R} \tag{7}$$

where L is the node lifetime and t_R is the worst case reaction time. The design goal is to maximize the Quality ratio. Fig. 11 shows the Quality ratio for the simulated sampling rates. The gain in the node lifetime by decreasing the duty cycle is not large enough to overcome the increment in inactive time. The advantage of the adaptive sampling rate over fixed sampling rate solutions can be clearly seen as a higher Quality ratio. Although the lifetime of the node for adaptive sampling rate is lower than the lifetime of the node with 1×10^{-3} Hz sampling rate (Fig. 10), we accomplish that the worst case reaction time in average is lower.

This adaptive approach gives a lifetime prolongation compared to the continuous gas monitoring of 449 times. Another important feature is that the inactive times of the sampling rates we combine (Fig. 10) are still acceptable for practical system implementation, like the one depicted in Fig. 6 and 7. Worst case reaction time of 16 min occurs only for two hours in the day, i.e. when the system indicates that there are no events in the ambient.

We clearly see enormous potential of prolonging the networks lifetime by using the designed low-power nodes in adaptive sampling mode. Bibliography doesn't show any example of a WSN for IAQ that could be autonomous for several years on batteries. De Vito *et al.* [12] are introducing on-board computations to calculate the gas concentration and decide whether the information should be transmitted or not. Their algorithm consumes 2.5 mA for 25 ms, for each operation phase. They are predicting 113 days of network lifetime. On the other hand, we base our system on the recognition of interesting events using a PIR sensor to adjust the sampling rate of the sensor data and we justify the introduction of additional power consumption by the PIR sensor to prolong the node lifetime to more than two years.

D. Experimental Testbed

To verify the simulation results in practice, in March 2012 we deployed a WSN with 36 nodes in a 4-story renaissance building in the center of Bologna, Italy, and used as a testbed for the FP7 project 3ENCULT. Fig. 12 shows the first floor of the building with deployed nodes (red squared with node ID number). By the time of submitting this paper, the network has shown continuous functionality, with actual power consumption which confirms the model presented in Section IV.

VI. Conclusion

This work addressed the concept of a smart WSN capable of monitoring indoor air quality and dangerous situations. The main goal of our approach is the energy consumption reduction on sensor level, node level and network level. To achieve this goal, the node consumes a very low sleep current (only 8 μA) and can perform dynamic gas sampling. In addition, we reduce the activity of the node and of the MOX gas sensor using the information about people presence from the PIR sensor and alarm messages from the other nodes in the network. We guarantee the reduction of power consumption without affecting reliability of the service. Simulations on an application scenario with a conservative power management strategy where activity of the gas sensor has been fixed (long enough to reach the asymptotic region of the transient behavior) show how the approach strongly increased lifetime of the network to several years with just 2 AA batteries (in respect to several days when the gas sensor is continuously driven). The initial study on the transient behavior of the gas sensor shows that its lowest resistance highly correlates with the asymptotic values and gives an option to further decrease the heating time which indicates power savings of two orders of magnitude. This requires further calibration and validation of the gas sensor in our future work. We should define the minimal time the sensor should be heated and find the threshold values in order to get a reliable information about the monitored gas concentration. Having that information, we can approach the issue of choosing a proper sampling rate set for the gas sensor that satisfies both long network lifetime and low reaction time.

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