

Wireless Sensor Networks for Distributed Chemical Sensing: Addressing Power Consumption Limits with On-Board Intelligence

Saverio De Vito, Paola Di Palma, Carmine Ambrosino, Ettore Massera, Gianbattista Burrasca, Maria L. Miglietta, Girolamo Di Francia

Abstract— Chemicals detection and quantification is extremely important for ensuring safety and security in multiple application domains like smart environments, building automation, etc.. Characteristics of chemical signal propagation make single point of measure approach mostly inefficient. Distributed chemical sensing with wireless platforms may be the key for reconstructing chemical images of sensed environment but its development is currently hampered by technological limits on solid state sensors power management. We present the implementation of power saving sensor censoring strategies on a novel wireless electronic nose platform specifically designed for cooperative chemical sensing and based on TinyOS. An on-board sensor fusion component complement its software architecture with the capability of locally estimate air quality and chemicals concentrations. Each node is hence capable to decide the informative content of sampled data extending the operative lifespan of the entire network. Actual power savings are modeled and estimated with a measurement approach in experimental scenarios.

Index Terms— Wireless Chemical Sensing, Electronic noses, Sensor censoring, Power saving.

I. INTRODUCTION

Pollutant and toxic gases affect human health in multiple scenarios. Their effects can vary from localized, low intensity to systemic with potential life threats, depending mainly on exposure time and concentrations. Hazardous gas, like explosives or flammable ones are also source of increasing concern for security reasons due to their possible use in terrorists attacks to military installations. Some of them are currently in use or are foreseen to be used as energy carrier for automotive transports and so their diffusion is expected to grow significantly, for example, hydrogen powered car refilling stations could become very common in the near future [1]. The capability to detect and monitor the presence of

such substances in the work or living environments, being indoor or outdoor, is thus of paramount importance in multiple applicative scenarios and should be considered as a potential life saving assets. Unfortunately, the characteristics of chemical signal propagation make the use of single measurement point solutions unfeasible and mostly inefficient. Actually, propagation of chemical plumes in real environments is primary related to complex fluid dynamics effects (e.g. turbulence) with diffusion being negligible in many circumstances [2]. Actually, diffusion velocities of gas molecules are too slow to transport chemical signals under many conditions. As such, gas concentrations in real environment can easily become very difficult to predict both in space and time domain.

Just as an example, the plume generated by an H₂ spill in a hydrogen based car refilling station could move in rather unpredictable paths and the probability of a single solid state chemical sensor to be hit by it with a significant concentration in a timely way could be considered negligible.

Recently researchers began to tackle these scenarios with novel approaches that refer to two main classes. A first approach is based on the use of a moving detector. Together with appropriate modeling information these detectors can follow random paths exploring a particular environment before being hit by a chemical plume [3-4]. After that, by using chemical spills search algorithms, often biomimetic, they try to detect the source of contamination (source declaration problem). The other approach, basically rely on the use of multiple, low cost and autonomous distributed fixed detectors, that try to cooperate in reconstructing a chemical image of the sensed environment [1][5-7]. Both approaches could maximize probabilities to detect and quantify appropriately the presence of hazardous or toxic gas in environment with different specificities.

Advantages of distributed approach are identifiable in flexibility, scalability, enhanced signal to noise ratio, robustness and self healing. Several sensors node can be placed in different locations, each one with its own characteristics in terms of environmental conditions (air flow, temperature, humidity, different gas concentration, etc.) contributing to describe more thoroughly the environment in which they are embedded. Each smart chemical sensor, composing the distributed architecture has its own communication capabilities and its information is available for

Manuscript received Feb 4 2010. S. De Vito, E. Massera, G. Burrasca, M.L. Miglietta, G. Di Francia are with Italian National Agency for New Technologies, Energy and Sustainable Development (ENEA), Portici Research Center, P.le E. Fermi, 1, 80055 Portici (NA) – Italy . E-mail: {[firstname.familyname](mailto:firstname.familyname@enea.it)}@enea.it, (corresponding author : S. De Vito ph: +39 081 7723364; fax: +39 081 7723344; e-mail: saverio.devito@enea.it). S. De Vito is also with University of Cassino, DAEIMI Dept., Via G. Di Biasio, 43, 03043, Cassino, Italy.

P. Di Palma, C. Ambrosino are with National Research Council, CNR-ISAFOM, via Patacca,85, 80056 Ercolano (NA) – Italy.

more than one client. The network can adapt itself to a variable number of chemical sensor improving reliability. If a sensor fails, the network can estimate its response on the basis of the previous behavior and of the response of the closest sensors while being able to self-heal the network structure by reconstructing routing trees [8]. Sensor calibration could be performed by temporarily adding other reference sensors or, thanks to data fusion techniques, using self recalibration strategies. Practically, the development of application specific algorithms could allow self calibration by exploiting networked cooperation in a totally unmanned fashion [9]. A distributed architecture means also that every sensing node has computing capabilities; it can provide diagnostic services and it can elaborate strategies, for instance, to improve the stability of its metrological characteristics. In particular this can be significant for implementing drift correction, accommodating a paramount problem in solid state chemical sensing.

The characteristics of an optimal sensor for distributed chemical sensing should include low power operations capability, low cost, long term reliability and stability; additionally it should also be easy to integrate with simple signal conditioning schemes. Depending on the application, the sensor should possibly express good specificity properties and very low detection limits. By far, this depiction applies more to an ideal device than a real one, in fact, no current chemical sensor technology seems near to obtain such results simultaneously [10-11].

In particular, the well known metal oxide chemical sensor technology (MOX) requires high working temperatures and, in fact, they are mostly coupled with micro-hotplates used to increase the temperature of the sensitive layer [12]. This represent a serious issue for their use in wireless chemical sensing nodes because their average power consumption is in the range of 200-800mW with continuous operation. Instead, polymer based chemiresistor, resonators and mass sensors (QMBs, SAWs) are usually operated at room temperature [13-16]. Although they are not as common as their MOX counterparts, their low power operation capability can be recognized as a huge advantage with respect to the other technologies especially when VOC (Volatile Organic Compounds) detection is concerned [17]. Unfortunately they may not be as efficient at very low concentrations and most of them are significantly affected by humidity.

Since a decade, polymer/nanocomposites reactivity to chemicals have been also applied to the development of passive resonant sensors that are capable of wireless remote operations in a very simple way [18]. LED/Polymer based optical sensing can be an extremely interesting solution for all application where high limits of detection are not an issue because of very low cost, reliability, and very low power demand [7], [1]. However in order to obtain suitable sensitivity in most application Laser source should be used and this may increase significantly both costs and power needs. Practically all solid state sensors are widely affected by being not specific, this issue has been tackled with the widespread electronic nose design often turning it into an advantage for mixture classification applications [10].

Current e-nose are not designed to tackle distributed chemical sensing problem, however during last years a number of novel approaches have been proposed and experimented. This field is hence rapidly evolving exploiting the plethora of results obtained by researchers in wireless technology field. Bicelli et al. have investigated the use of commercial low power MOX sensors in a WSN network scenario for indoor gas detection applications. Their primary focus was the analysis and reduction of power consumption in order to meet DCS criteria. They suggested a particular heating procedure in an attempt to achieve a significant increase in the wireless sensor battery life (about 1 year) with sample period in the range of two minutes. Unfortunately this resulted in increasing the actual response time [19].

Pan et al. realized a single w-nose for online monitoring of livestock farm odours integrating meteorological information and wind vector [5]; detection performances and power consumption have been reported so it was not possible to estimate autonomous life expectation. Warmer et al. recently presented a 4 MOX sensors based WCSN network for flammable detection in military docks but power needs, restrict the application to the availability of power mains [20].

During the last years, we. have developed a wireless electronics nose platform equipped with four polymeric sensors and based on TelosB mote using TinyOS operating system. The platform, make use of room temperature operating low power chemical sensors that extends the entire sensory network lifespan.

In this work, on-board intelligence is implemented to provide the basis of sensor censoring strategy that allow for transmission of only informative data packets. We propose the use of such a strategy for achieve a dramatic reduction of the power needed for distributed chemical sensing network further extending its lifespan. The target scenario for the application of the proposed methodology is the distributed monitoring of indoor air quality and, specifically, the detection of toxic/dangerous VOC spills.

In the following, a description of the architectural features of the proposed platform is provided focusing on the design and test of on-board intelligence for power management. An instrumental investigation on the performance of the overall intelligent power management methodology has been carried out.

TABLE I: Sensor Array Composition

	Polymer Chemical	Structure
Sens1	Poly-(methylmethacrylate) (PMMA)	[CH ₂ C(CH ₃)(CO ₂ CH ₃)] _n
Sens2	Poly-(2hydroxyethylmethacrylate) (HEMA)	H(NHCH ₂ CH ₂) _n NH ₂
Sens3	Poly-(styrene) (PS)	(C ₆ H ₁₀ O ₃) _n
Sens4	Poly-(ethylenimine) linear(PEI)	[CH ₂ CH(C ₆ H ₅)] _n

II. WIRELESS SENSOR NETWORK ARCHITECTURE

The developed platform is a wireless network consisting of spatially distributed autonomous devices that use sensors to monitor and detect the presence of organic vapors in air.

The modules were designed to operate in a mesh shaped network in order to pursue the final goal of building an olfactive image of a sensed environment by means of a distributed platform connected to a PC for data management purposes (Fig. 1).

A. Modules Sensors Array

The sensing board is based on four polymer-carbon black sensors (see Table I), a class of chemical detecting devices that have been already selected for electronic noses applications [13-18]. Their selectivity can be adapted via the use of the wide range of polymeric materials and conductive fillers available [14].

In our opinion, this class of sensing devices is particularly suitable for the applications in distributed chemical sensing application for their interesting low power and rapid switch on characteristics. Their mechanism of response is, at its simplest level, based on swelling. When the polymer film, within which conductive particles have been dispersed, is exposed to a particular vapor, it swells while absorbing a varying amount of organic vapors depending of polymer's type.

The swelling disrupts conductive filler pathways in the film by pushing particles apart and the electric resistance of the composite increases [16]. As a result of this room temperature operating mechanism, they exhibit very low power consumption and, if properly conditioned, a nice stability. However, they suffer for poor selectivity and sensitivity.

In order to obtain a suitable voltage signal, i.e. showing proportionality to sensor resistance variation, a simple resistance to voltage converter signal conditioning system has been designed. Suitable choice of circuit parameters allow the proper operation of the board within a wide range of base resistance. In Fig.2 the functional scheme of the board is shown.

The overall sensing subsystem is then directly connected to four A/D input ports provided by the core mote of the proposed platform, a commercial Crossbow TelosB mote.

B. Core Mote

The commercial Crossbow TelosB platform is a research oriented mote platform that has shown its operative potential over time [21]. Each TelosB node is powered by 2 AA batteries for standalone operations while it can be powered by a standard USB interface for its usage as a datasink related module. The chosen platform is based on a Texas Instruments MSP430F1611 microcontroller which is a 16-bit RISC processor featuring 10kB of RAM, 48 kB of flash and 128B of information storage. It operates at 1.8V and allows for very low power consumption states from which it can recover in few ms. It also has 8 built-in (ADC) channels providing also DAC capabilities. The basic node is equipped with a set of

commercial sensors among which the SHT11 humidity and temperature sensors that can be very useful in chemical sensing applications both as a primary information source and for multivariate sensor calibration. The embedded low power radio, Chipcom© CC2420, represent the kernel for 802.15.4 protocols stack support.

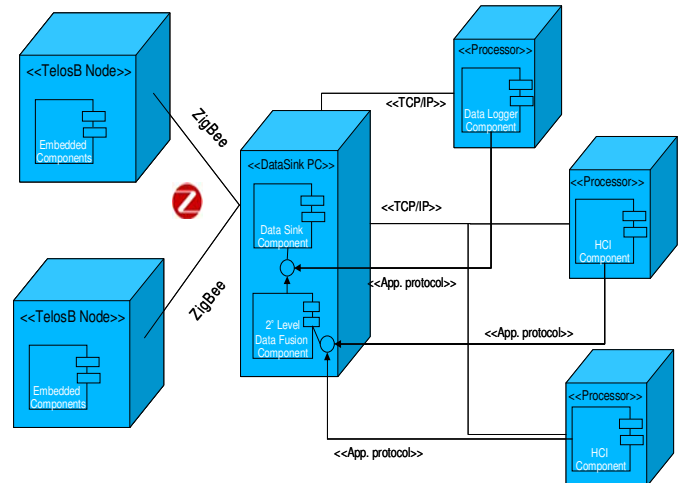


Fig. 1. UML Deployment diagram of the software architecture for the proposed platform

Basically, the choice of this module as the core mote is based on very low power sleep state of both MCU and radio sections, fast recovery and the availability of community support with a wide number of educational based users. Data transmission, in fact, is one of the primary power draining activity in WSN applications and the choice of a low power transmission with low power states and fast recovery is crucial.

C. DCSN Software Architecture

The heterogeneity of the practical applications and the limited energy availability required a careful design of the sw structure and protocols for the management of the wireless e-nose platform. The possibility to focus primarily on domain specific optimization, led to the choice of the TinyOS architecture as a run time support and operating system.

TinyOS is an open source operating system for WSN applications developed by University of California at Berkeley [22]. Essentially, TinyOS's component library includes network protocols, distributed services, basic sensor drivers, data acquisition tools – all of which can be further refined for custom applications. Specific software modules realize basic functionalities control of the sensor node, like access microcontroller registers, writing and reading from EPROM, the interface radio management for transmission and reception data. In particular the power management model of TinyOS allow for the automatic management of module subsystems switching among active, idle and sleep phases. Often, provided that the custom sw design meet the TinyOS requirements, the programmer can focus on specific optimization letting the run time operate for general power

saving options.

A C derived language, NesC, is the reference programming language for TinyOS based programming. NesC rely on a component based programming module. Users can expand basic TinyOS functionalities building their own components relying on NesC itself. The executable code generated by the NesC compiler includes only the TinyOS modules actually needed by the custom applications, minimizing memory footprint.

Fig. 1 shows an UML deployment diagram of the overall platform software architecture from which its three layers design is clearly apparent. The first layer encompass all the embedded sw components that being developed in NesC, can make use of TinyOS directives to provide on board w-nose control and networking functionalities. In particular, the embedded component is responsible for pump ON/OFF operations control (optional, its presence depends on applications), sensors signal conditioning board control (ON/OFF switching), data acquisition and processing, and eventually data transmission and routing. At the second layer, a PC based component coded in Java capture data packets from a sensorless node that act as a datasink and is connected, via a USB connector, to the datasink PC. This component provides rebroadcasting features for distributing the data provided by the networked nodes over TCP/IP networks. The component has been developed by using as a core component the SerialForwarder class provided by the TinyOS standard installation. At the third level, multiple GUIs, also coded in Java, can provide visualization and recording features while remotely controlling relevant parameters for embedded sw operations (e.g. duty cycle parameters). Separate tabs provide visualization of raw data or pollutant concentration local estimations provided by each node. Actually, the overall architecture has been designed to host two possible pattern recognition and sensor fusion subsystems. The first interface defines methods to connect a sensors raw data processing component that will allow for local situation awareness. Actually it is connected to the local sensor fusion component that allows for the local estimation of pollutants concentration by using a trained neural network algorithm. The second interface, should provide second layer sensor fusion services, allowing for integrating estimation coming from the several deployed wireless e-noses actually cooperatively reconstructing an olfactive image of the environment in which they are deployed. The second layer sensor fusion algorithm and its implementing component is currently under design.

D. Duty Cycle and Power Consumption

The proposed platform has been designed for continuous real time monitoring of VOC with a programmable duty cycle including sensors data acquisition, processing and transmission toward data sink. Duty cycle parameters and in particular the length of each phase and the sampling frequency are fully programmable by the application designer, sample frequency can be set dynamically at run time by GUI . For this work it has been set to 1 sec.

In order to fully characterize the power consumption, we can easily separate the duty cycle in four separate phases each one having a different power need:

- 1) **Sleep** phase. In this phase each node is put asleep. MCU and radio are turned in stand-by mode;
- 2) **Sensing** phase. Sensors driving, data acquisition and ADC conversion is carried out;
- 3) **Computing** phase; Data processing is performed in order to prepare data to be transmitted towards datasink;
- 4) **Transmission/Reception phase:** the actual data transfer.

The whole embedded software has been designed and implemented to optimize the battery life by controlling the duration of each phase and the activation of sensors driving electronics.

At any instant, a single module power consumption can be computed as a function of its microcontroller power state and whether the radio, pump, sensor driving electronic are on, and what operations the active MCU sub-units are performing (analog to digital conversion). By using appropriate programming models, e.g. relying on split-phase operations, it's possible to best utilize the features provided by TinyOS to keep the power consumption to a minimum. In particular, as regards as radio stack management, we have chosen to rely on the LPL – Low Power Listening algorithm. As such, node radio can be programmed to switch on periodically just long enough to detect a carrier on the channel. If a carrier has been detected, then the radio remains on long enough to detect a packet to be routed to the data sink for mesh shaped networking. After a timeout, the radio can be switched off.

III. RESULTS

In this work our goal is to present a sensor censoring (see ref. [23-25]) power management strategy based on on-board sensor fusion component for long-term operation real time distributed chemical sensing with wireless electronic noses.

TABLE II: Core mote consumption in different phases of the Duty Cycle

Operation phase	Time [ms]	Current request [mA]
Radio Sleep (RS)	$T_{RS} = 888$	$I_{RS}=0,012$
Radio Wakeup (RW)	$T_{RW} = 7$	$I_{RW}=5$
Acquisition (A)	$T_A = 37$	$I_A=19$
Computing (C)	$T_C = 25$	$I_C=2,5$
Transmission (T)	$T_T = 68$	$I_T=18$

Our approach, is based on a simple sensor fusion component designed to locally detect chemical species presence, simultaneously estimating their concentration. In this way, the mote is able to assess if the data are informative and apply sensor censoring, i.e. to decide whether to transmit it or not. Alternative approaches, are based on data buffering (store & forward), i.e. sending data samples collection in

burst, extending latency (see ref. [24]). Unfortunately, in real time chemical sensing this approach is not feasible for obvious reasons: sampled data, if deemed significant, should be transmitted as soon as possible. We wanted to assess the feasibility and potential benefits of using such an approach in distributed chemical sensing by measuring the actual power consumption of a sensor node in a star shaped networking configuration to assess the module operative lifespan.

The measurement setup is based on a Tektronix TDS 3032 digital oscilloscope set to measure V_{shunt} on 10 Ohm shunt resistance and to let us derive current flows (fig. 2).

In its simplest configuration with sample frequency set at 1 Hz, the sensor node, as mentioned above, remain in sleeping mode for most of the time (T_{RS} time interval). In this phase a current I_{RS} , measured as $12\mu A$, is drawn. . During the T_{WR} wake up period the sensor node turns on the chip radio awakening from the sleep mode. In this stage we measured a 5 mA mean current draw. After that, the system set up itself for data capture and conversion with a mean current of 19 mA. Even in this stage, provided that data are sent every acquisition cycle, radio activity is the main source of power consumption. In fact power consumption in the active phase, is dominated by radio activity until switch off timeout inset; after ADC converter timeout, it can be measured as 18 mA. Eventually the RF circuit is turned off again and the state change from “Transmission” mode to sleeping mode.

Fig. 3 show the detailed evolution of the TelosB drawn current during acquisition, processing and data transmission of sensors data while Table II shows the TelosB consumption in terms of measured currents during each operating phase. Although in the operating conditions polymeric sensors power consumption is negligible, the overall electronic conditioning board, requires significant current draw. Actually, we have measured, under normal operating conditions, that the current needed for sensor array driving and signal conditioning board is equal to 38 mA (see Table III). The adopted experimental solution provides the implementation of solution for the control of power supply of the signal conditioning board. A digital signal obtained from a TelosB digital output drives a switch that lets the electronics power supply to switch on only during the time slice in which data capture take place. The implementation of such strategy is only made possible by the peculiar sensor response mechanism of the non-conductive polymer sensors. In fact swelling is only negligibly affected by actual sensor power up so that sensors doesn't need warming up before their resistance could be sampled. Conversely MOX sensors should be carefully driven to achieve their best response characteristics [19].

Table III: Platform Signal Conditioning Board Consumption

Operation phase	Time [ms]	Current request [mA]
Operating condition	$T_{ON}= 30$	38

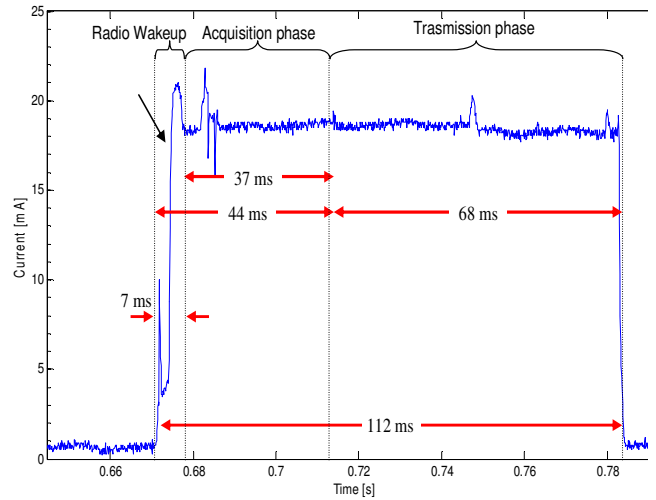


Fig. 2. Current absorbed by TelosB in its active operating phase, in particular during the radio wakeup, sensing and transmission phases in a complete cycle.

Usually, module lifespan can be estimated using the mean current consumption, namely $I_{cc,mean}$, of the wireless sensor, considering batteries capacity, conversion efficiency and power supply output voltage gain.

In their related work, Bicelli et al. suggest the use of a simple reference formula in order to compute $I_{cc,mean}$ by averaging current consumption over the multiple phases of a module duty cycle [19]. In order to compare results with that specific work, we set the sampling period T to one second, furthermore, initially, no sensor fusion take place and data are sent to datasink at the end each sampling cycle. The mean current value, $I_{cc,mean}$, obtained under the TelosB operating conditions described above, can be computed according to (1) by using the current measured in the proposed setup.

$$I_{cc,mean} = \frac{T_{RS}}{T} I_{RS} + \frac{T_{RW}}{T} I_{RW} + \frac{T_A}{T} I_A + \frac{T_T}{T} I_T \quad (1)$$

Table II summarize the results of performed measurements. According to it, I_{RS} is the current drawn from the entire platform during sleeping phase. Circuitry elements that must be turned on during the acquisition phase (e.g. microcontroller, interface circuits, ADC etc.) require a total $I_A = 19$ mA contribution ; however, the radio, that must be switched on for communication purposes, account for the most of I_A current contribution during active phase.

In fact, assessment of the duration of T_A phase has been conducted in a previous step by avoiding transmission phase. The actual current drain in T_A phase is due to the simultaneous consumption of data capture and radio equipment. We found that the reported duration of T_A is mainly due to ADC timeout length. Furthermore, for our goal there is no need of assessing precisely when the data transmission occur.

Neglecting conversion efficiency, battery life (BL) can be computed as a function of the battery capacity C and total current draw. For our w-nose, C is equal to 3500mAh while total current is equal to the sum of mean current absorbed by

conditioning board $I_{b,mean}$ ($30/1000 \times 38 = 1.14 \text{ mA}$) and the $I_{cc,mean}$ (1.97 mA), related to the core mote, computed using (1). Expressing BL as the ratio $C/(I_{cc,mean} + I_{b,mean})$, we can estimate that the overall e-nose battery life, with sampling and transmission frequency of 1 Hz, is roughly 47 days. In order to comment on comparison of our results with those reported by literature we should take into account that this platform is equipped by a small array of sensors while typical results are reported for single sensors wireless nodes. Anyway extending the sample period to 10 seconds, hence losing real time characteristics, this basic setting will account for a battery life in excess of 1 year.

A. Power saving using sensor censoring

As previously mentioned, a local sensor fusion component can classify a sampled sensor response pattern to assess the significance of the sampled data. The further power consumption needed by these computational activities should be taken into account to evaluate a trade off that depends basically on the rate of significant events occurrence. Actually, in most chemical sensing scenarios the probability p of a significant event to occur (e.g. chemical spills) is expected to be very low, while the timely transmission of relevant data is needed for rapid situational awareness in security application or for multiple mote data fusion at data sink. These constraints doesn't permit the relaxation of the latency parameter. It is also important here to recall that sensor fusion at mote level is needed for the intrinsic non specificity of solid state chemical sensors that will make threshold based approach almost useless both for chemical identification and quantification.

In order to perform an experimental check of the exposed concepts in distributed gas sensing scenarios, we have designed and implemented an ad-hoc lab scale experiment. We have designed and developed a sensor fusion component that have been trained for a distributed pollutant detection application with wireless e-noses. Deployment network topology was star shaped.. Hence, We have evaluated the power savings obtained by using sensor censoring in this common application scenario. Actually, We assumed a general chemical sensing problem characterized by the presence of two pollutants whose toxic/dangerous concentration limits are different. To save batteries energy, The single mote should be able to decide whether to transmit or not the sampled data on the basis of the concentration of the two gas estimated by sensor responses. The e-noses sensor arrays have been exposed to four concentrations levels of Acetic Acid and Ethanol in a controlled environment setup and their responses, sampled by the motes, have been recorded to build a suitable data set. Concentration levels have been chosen to be [225, 450, 900, 1800] ppm for Acetic Acid and [200, 500, 1000, 2000] for Ethanol while relative humidity was fixed to 30%. Five complete exposure/purge cycles have been conducted and instantaneous response to base response ratio of each sensor was used as descriptive features. We have designed and

implemented a three layer feed forward neural network (FFNN) component using NesC. FFNN architecture have been chosen on the basis of considerations about its peculiar characteristics. In facts, FFNN shows a high degree of flexibility and a high capacity in pattern recognition sense. Their computational footprint, at least in the operational phase, is relatively small; furthermore, their highly compact internal knowledge representation paradigm allow for a very limited memory footprint. The component has been linked to the platform embedded software architecture so to run onboard. The neural network component design foresee 4 input neurons, ten hidden layer neurons and two output neurons whose outputs indicate concentrations of the simulated pollutants. The network component has been then loaded with networks weights obtained by training an identical model in MATLAB with the recorded dataset. so to reach a reasonable point-to-point real time estimation of concentrations of different analytes, thus simultaneously solving a classification and regression problem.

Practically, normalized steady state response have been used as training set while the remaining samples have been used for validation purposes. By choosing this particular training dataset split, we set apart a significant number of test samples; on the other hand, we can expect significant errors to occur in the estimation of transient samples. Since estimation error is averaged on all samples, transient cause a significant hit on the chosen synthetic performance estimators. In this laboratory based setup, the proposed architecture performance was evaluated by dividing validation set Mean Absolute Error (MAE) by analyte concentration range span , obtaining, despite the above mentioned setup, a 6% (standard deviation: 10%) value for Acetic Acid concentration estimation problem and 11% (standard deviation: 11%) for the Ethanol problem (see Fig. 4). Preliminary performance operative tests with a simpler architecture were also conducted and results were reported in [26], anyway significantly performance boosting, in particular as regarding dynamics, could be achieved by using a two stage detector/quantifier approach with tapped delay architectures as reported in [27].

In this paper, however, we focus on sensor censorship strategy transmission vs. Processing trade off that would be hampered by sensor fusion component complexity. For this reason, assessment of the memory footprint increase, resulting from the implementation of the local sensor fusion approach, has been conducted and results has been reported reported in table IV. approach, has been conducted and results has been reported reported in table IV.

TABLE IV: Memory footprint increase in the Embedded component resulting from the linking of sensor fusion neural component

Algorithm	Bytes in ROM	Bytes in RAM
Basic	20380	574
Basic+NN comp.	27340	910

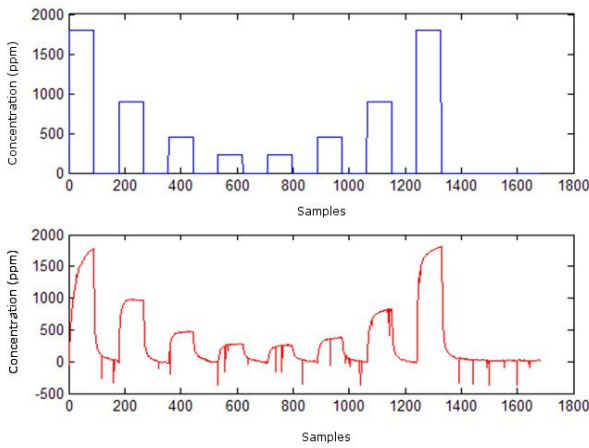


Fig. 3. Acetic acid concentration estimation (red) performed by the FFNN component plotted against true concentration (blue). X axis depict time (samples) while y-axis depicts real and estimated concentrations values.

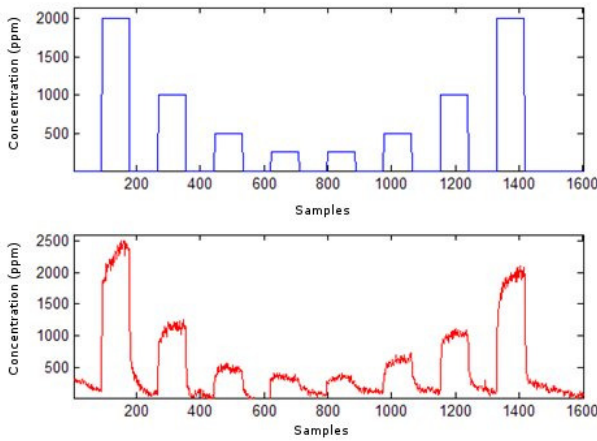


Fig. 4. Ethanol concentration estimation (red) performed by the FFNN component plotted against true concentration (blue). X axis depict time (samples) while y-axis depicts real and estimated concentrations values.

As regards as the computational footprint impact we can expect several hyperbolic tangent function calls as well as multiplications and sums, the number of which depending only on the particular network architecture. For the current four hidden layer neurons architecture this figures are reported in table V.

TABLE V: Computational Complexity in terms of functional calls.

Functional	Calls per each NN estimation
Tanh	10
Multiplication	76
Sum	82

Following a measurement approach, the execution of the NN sensor fusion component account for additional 2.5 mA consumption over a total time span of 25ms (function call overhead included).

In order to re-assess total power consumption we write the (1) again by taking into account computing phase.

$$I_{cc,mean}^{NN} = I_{RS} \left(1 - \frac{T_{RW} + T_A + T_T + T_C}{T} \right) + I_{RW} \frac{T_{RW}}{T} + I_A \frac{T_A}{T} + I_T \frac{T_T}{T} + I_C \frac{T_C}{T} \quad (2)$$

This equation provides the mean current supplied by the batteries in case of significant event occurrence: the mote perform signals conditioning and data sampling, data fusion by means of NN and data transmission every T seconds.

Using a Bernoulli random variable $X \sim B(1, p)$ which would model the result of the computation performed by the NN to verify whether transmit the acquired data on the radio channel, eq. (2) can be rewritten as:

$$I_{cc,mean}^{NN} = I_{RS} \left(\frac{T_{RS}' p + T_{RS}'' (1-p)}{T} \right) + I_{RW} \frac{T_{RW}}{T} p + I_A'' \frac{T_A}{T} (1-p) + I_A' \frac{T_A}{T} p + I_T \frac{T_T}{T} p + I_C \frac{T_C}{T}. \quad (3)$$

Where T_{RS}' , T_{RS}'' are respectively:

$$\begin{cases} T_{RS}' = T - T_{RW} - T_A - T_T - T_C \\ T_{RS}'' = T - T_A - T_C \end{cases} \quad (4)$$

By exploiting equation (3) we can finally discuss the advantages of NN based sensor censoring for the implementation of power saving strategies in the proposed architecture.

Worst case is obtained when $p = 1$, i.e. when all samples refers to significant events, then the mean current computed using (3) is obviously greater than the one calculated by (1) i.e. $I_{cc,mean}^{NN} = 2.013 \text{ mA}$. However, by equating (1) and (3) and selecting p as independent variable, we obtain:

$$p = 0.97 \quad (5)$$

The obtained value represents the percentage threshold of significant event under which the NN based sensor censoring become more efficient as regards as power management. This computed threshold level make the use of the proposed approach feasible for most of the analyzed distributed chemical sensing scenarios.

In industrial chemical spills monitoring, even considering false positive generation, it is reasonable to expect values of p that reflect a number of only a few (<100) significant samples a day. This is true even in the case of performing only rough local concentration estimations and being very conservative in the censoring criteria. Censoring criteria, i.e. spiking threshold, should be chosen exploring the trade-off among

sensitivity and false positive rate considering the danger/toxicity level of the target gas. With this regards, danger/toxicity levels should, of course, be taken into account also during training selecting an appropriate interval that match working conditions. The nature of second level sensor fusion subsystems that collect data from the different networked nodes also has significant implications in the threshold choice. Just as an example, a second level sensor fusion subsystem, may decide to initially ignore time isolated detection reported from a single node waiting for a number of received spike to accumulate before declaring an emergency or tagging the node as malfunctioning.

For an experimental evaluation, using the above mentioned setup and allowing a small slack to the network estimation of ethanol (detection threshold on NN response=10ppm w.r.t. a 2000ppm max exposure level) we obtain a false positive rate of 5% for Ethanol and less than 1% for Acetic Acid. In case of no positive events during node battery lifetime, a reasonable expectation in safety oriented leakage detection scenario, a proposed node can be expected to experiment a maximum operative lifespan that is very near to the intrinsic limit now dominated by the power needed by signal conditioning board. In particular, considering a $p=0.01$, the expected lifetime computed by taking into account (3) reach 113 days (110 days for a $p=0.05$), that is a rather interesting value for a 4 sensors wireless electronic nose with real time operating characteristics.

IV. CONCLUSIONS

We have developed a distributed chemical sensor architecture based on intelligent electronic nose motes that rely on room temperature operating solid state polymer sensors. The proposed w-noses have proven capable, if properly trained in lab conditions, to locally infer chemicals presence and their specific concentrations. This capability can be used for the implementation of sensor censoring strategies. i.e. to decide on sample data significance, so to improve power management by simultaneously avoiding unneeded transmissions and retaining low latency characteristics.

Influence on mean current drawn by the on-board sensor fusion component have been modeled and discussed in different scenarios characterized by different event frequency.

By using a measurement approach we have demonstrated that this capability can allow for remarkable extension of network operating lifespan in real time distributed chemical sensing applications that are currently strongly limited by both sensor arrays and data transmission power needs. However, sensors driving and signal conditioning stage are currently in a prototype stage so we expect a significant reduction in power needs in the following releases that could allow the proposed platform to reach the 1 year target lifespan.

ACKNOWLEDGMENT

This work is partly funded by P.O.R. Campania 2002/2006 mis. 3.17, grant no.4997 "Sistema Integrato Multisensoriale

per il Monitoraggio Ambientale" (SIMMA-ICT) and by project FP7-ENCOMB.

REFERENCES

- [1] C.Grimes,K.G. On, O. K. Varghese, X. Yang, G. Mor, M.Paulose, E. C. Dickey, C. Ruan, A Sentinel Sensor Network for Hydrogen Sensing, *Sensors*, 3, 69-82 (2003).
- [2] T. Nakamoto, H. Ishida, Chemical sensing in spatial/temporal domains *Chemical Review*, 108 (2) pp.680-704 (2008).
- [3] Achim J. Lilienthal, Amy Loutfi and Tom Duckett, Airborne Chemical Sensing with Mobile Robots. *Sensors*, 6, pp. 1616-1678 (2006).
- [4] Achim J. Lilienthal and Tom Duckett, Building Gas Concentration Gridmaps with a Mobile Robot. *Robotics and Autonomous Systems*, 48:1, 1, pp. 3-16 (2004).
- [5] Pan L., Rui L., Shanghong P., Chai Y., and Yang S.X. A wireless electronic nose network for odours around livestock farms, In: Proc. Of 14th International Conference on Mechatronics and Machine Vision in Practice, M2VIP 2007, Xiamen, pp. 211-216 (2007).
- [6] S. De Vito, E. Massera, G. Burrasca, A. Di Girolamo, M. Miglietta, G. Di Francia, D. Della Sala, "TinyNose: Developing a wireless e-nose platform for distributed air quality monitoring applications", *Sensors 2008 IEEE Conf.*, Oct. 26-29, Lecce, Italy, pp. 701-704 (2008).
- [7] R. Shepherd, S. Beirne, K.T. Lau, B. Corcoran, D. Diamond, Monitoring chemical plumes in an environmental sensing chamber with a wireless chemical sensor network, *Sens. Actuators B Chem.*, 121 (1), pp. 142-14 (2007).
- [8] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci: "Wireless sensor networks: a survey", *Computer Networks*, vol 38, pp: 393-422 (2002).
- [9] W. Tsujita, A. Yoshino, H. Ishida and T. Moriizumi, Gas sensor network for air-pollution monitoring, *Sens. Actuators B: Chem.* 110, pp. 304–311 (2005).
- [10] K. Arshak, E. Moore, G. M. Lyons, J. Harris, S. Clifford, "A Review of gas sensors employed in electronic nose applications", *Sensor Review*, 24 (2), pp.181-198, (2004).
- [11] D. Diamond,S. Coyle, S. Scampagnani, J. Hayes, *Wireless Sensor Networks and Chemo-/Biosensing*, *Chem. Rev.*, 108 (2), pp 652–679 (2008).
- [12] N. Barsan, U. Weimar, Conduction model of metal oxide gas sensors. *J. Electroceram*, 7 (3), pp. 143–167, (2001).
- [13] L. Quercia, F. Loffredo, M. Bombace, I.Nasti, G. Di Francia, "Effects of thin film polymer composite preparation on vapor sensing devices characteristic", *Sensors. Actuators B*,111-112, p.166-170 (2005).
- [14] L. Quercia, F. Loffredo, B. Alfano, V. La Ferrara, G. Di Francia, "Fabrication and Characterization of carbon nanoparticles for polymer based vapor sensors", *Sensors.Actuators B*, 100, p. 22-27 (2004).
- [15] Plum T.J., Saxena V., and Jessing J.R. Design of a MEMS Capacitive Chemical SensorBased on Polymer Swelling, *Proceedings of 2006 IEEE, Workshop of Microelectronics ad MicroDevices*, April 14, Boise, Idaho, USA (2006).
- [16] E. J. Severin, B. J. Doleman, N. S. Lewis, "An investigation of the concentration dependence and response to analyte mixtures of carbon black/insulating organic polymer composite vapor detectors", *Anal. Chem.*, 72, pp. 658-668 (2000).
- [17] S. C. Ha, Y. Yang, Y.S. Kim, S.H. Kim, Y. J. Kim, S. M. Cho, " Environmental temperature independent gas sensor array based on polymer composite", *Sensors and Actuators B*. 108, pp. 258-264, (2005).
- [18] Yoon H., Xie J., Abraham J.K., Baradan V.K., and Ruffin P.V. Passive wireless sensors using electrical transition of carbon nanotube junctions in polymer matrix, *Smart material and structures*, 15 (1), pp. 14-20 (2006).
- [19] S. Bicelli, A. Depari, G. Faglia, A. Flammini, A. Fort, M. Mugnaini, A. Ponzoni, V. Vignoli, S. Rocchi, "Model and Experimental Characterization of the Dynamic Behavior of Low-Power Carbon Monoxide MOX Sensors Operated With Pulsed Temperature Profiles", *IEEE Trans. Instrum. Meas.*, May, 2009, Vol-58, N.5, pp. 1324-1332
- [20] Becher, C., Kaul, P., Mitrovics, J., Warmer, J.,The detection of evaporating hazardous material released from moving sources using a gas sensor network, *Sensors and Actuators, B: Chemical*, Volume 146, Issue 2, 29 April 2010, Pages 513-520

- [21] J. Polastre, R. Szewczyk, "Telos: Enabling Ultra-Low Power Wireless Research" Proc. International symposium on Information processing in sensor networks, 2005.
- [22] TinyOS Website : <http://www.tinyos.net>
- [23] E.Y. Chang, A. Jain "Adaptive Sampling for Sensor Networks", In: Proc. Of the First International Workshop on Data Management for Sensor Networks, DMSN 2004, August 30th, Toronto, Canada, 72, 10-16 (2004).
- [24] C.Rago,P.Willett,andY.Bar-Shalom, "Censoring sensors: A low-communication rate scheme for distributed detection," IEEE Trans.Aerosp.Electron.Syst.,vol.32,no.2,pp.554-568,Apr.1996.
- [25] Appadwedula, S., Veeravalli, V.V., Jones, D.L., Decentralized detection with censoring sensors, IEEE Transactions on Signal Processing 56 (4), pp. 1362-1373
- [26] Saverio De Vito, Gianbattista Burrasca, Ettore Massera, Mara Miglietta, and Girolamo Di Francia, Power Savvy Wireless E-Nose Network using In-Network Intelligence, Proceedings of 13th ISOEN , AIP Conference Proceedings, Vol. 1137, pp. 211-214. ISBN: 978-0-7354-0674-2
- [27] Saverio De Vito, Anna Castaldo, Fausta Loffredo, Ettore Massera, Tiziana Polichetti, Ivana Nasti, Paolo Vacca, Luigi Quercia, Girolamo Di Francia, Gas concentration estimation in ternary mixtures with room temperature operating sensor array using tapped delay architectures, Sensors and Actuators B: Chemical, Volume 124, Issue 2, 2007, pp. 309-316



Saverio De Vito received his MS in Informatics Engineering from University of Naples "Federico II" in 1998. During 1998 and 1999 He was a research fellow at Artificial Vision and intelligent systems laboratory of the above university working on breast cancer computer aided diagnosis. From 1999 to 2004 He was in ICT engineering as a R&D project manager in the framework of satellite based telemedicine, earth observation and distance learning projects. In June 2004 he joined ENEA, as a researcher. He is currently based in Portici research center. His research interests include statistical pattern recognition, artificial olfaction, wireless sensor networks and computer aided diagnosis. Since 2005 he is contract professor of Applied Informatics at University of Cassino.



Gianbattista Burrasca graduated in Electronics Engineering at University of Ancona (Italy) in 2000; its thesis was on electromagnetic diffraction problems. In March 2001 he began activities in photovoltaic systems design and electronic circuits design for photovoltaic applications, employee in a private company. Since October 2004 he is a researcher at ENEA. From 2004 to 2009 he was focusing its activities on Ink-Jet techniques for functional material's deposition and embossing techniques. Furthermore he also worked on electronic interfacing for sensors finalized to electronic nose development. Since 2009, he is involved in electronic systems development for testing of heat exchange components in nuclear fusion reactors.



Paola Di Palma received her MS in Electrical Engineering from University of Cassino in 2009. She was a research fellow of CNR-ISAFOM and ENEA pursuing research on artificial olfaction and wireless sensor networks with applications to distributed olfactive nuisance detection, indoor air quality and power management in wireless sensor networks. She is now system designer for an engineering firm specialized in photovoltaic systems.



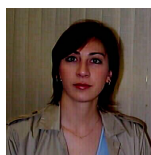
Carmine Ambrosino received his MS in Informatics Engineering from University of Sannio in 2007. During 2007 and 2008 he was fellow of GRACE laboratory of University of Sannio working on control automation systems for automotive applications. During 2009 he was fellow of CNR-ISAFOM and ENEA pursuing research on artificial olfaction and wireless sensor networks with applications to distributed olfactive nuisance detection, indoor air quality and power management in wireless sensor networks. He is now with CNR-ITIA developing software components for researches in control automation for manufacturing systems.



Girolamo Di Francia received his degree in Physics from the University of Naples "Federico II". In 1985 he started his research activity in the field of fabrication and characterization of semiconductor solar cells (c-Si, GaAs), formerly in the Ansaldo comp. in Genova, and then in the ENEA research center of Rome, where he was appointed full time researcher in 1988. From 1991 he joined the ENEA research center of Naples where, starting from 1992, he investigated porous silicon based devices. In 1996 he established there the Gas Sensor Laboratory mainly devoted to the fabrication and characterization of devices based on nanomaterials and on polymers nanocomposites.



Ettore Massera received his degree in physics from the "Federico II" University of Naples in May 1997. He has been working at the ENEA research center in Portici (NA) from June 2003. At present he is in charge of research activity on gas sensor devices based on nano-structured materials. Previously he worked on the study of thermal and optical properties of porous silicon at the physics Department of University of Naples.



Mara Miglietta received the B.S. degree in Chemistry from the Università degli Studi di Bari in 1997. In 1999 she joined ENEA as a Researcher working on environmental monitoring and on liquid and solid state NMR (HR-MAS, CP-MAS) of foodstuffs and polymers for food packaging. Since 2007 she works in the fields of nanotechnologies, specifically on polymer nanocomposites and conductive polymers for VOC sensing applications and physico-chemical characterization of nanomaterials.