ENVRI^{plus} DELIVERABLE

D1.6
RESULTS AND RECOMMENDATIONS FROM THE COMPARISON EXERCISE OF SENSOR EMBEDDED PROCESSING PRACTICES

WORK PACKAGE 1 – NEW SENSOR TECHNOLOGIES: INNOVATION AND SERVICES

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ABSTRACT

Small, generally low-cost sensors, that are deployed in unsupervised networks (or remote locations such as the ocean) are becoming more and more important across RIs and across domain. These kinds of sensors generally come equipped with data/signal processing capabilities that are generally stored in a microcontroller unit accompanying the sensing unit itself. This deliverable aims to sum up what are the main criticalities, issues and guidelines when applying these kinds of sensors in the field. Different applications and different sensors are examined in the deliverable ranging from low cost air pollution wireless sensor networks up to oceanic automated profilers. The result of such a comparison exercise is the highlighting of two main criticalities for which recommendations are provided:

1. Calibration of the sensors
2. Management of communications between the remote sensor and the user

Many sensors with embedded capabilities, especially low-cost ones, output data that must be carefully treated to have an effective value for the user. The deliverable shows, therefore, what are the best venues and methodologies to analyze these kinds of data and what are the pitfalls in the calibration procedures.

Many of the described sensors are often deployed in remote or unsupervised location and therefore it is of utmost importance to correctly approach the networking and communication capabilities to embed on the sensing platform. Depending on the amount of data produced and the type of sensor, this deliverable offers specific guidelines to manage this aspect.

Overall D1.6 reports the experience of CNR/ANAEE and partners (IFREMER, PLOCAN, CNRS, University of Bremen, CEA) developed within ENVRIPLUS with sensor embedded processing practices and gives a reference guide for any RI that wants to introduce this practice into its field measurements.

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PROJECT SUMMARY

ENVRIplus is a Horizon 2020 project bringing together Environmental and Earth System Research Infrastructures, projects and networks together with technical specialist partners to create a more coherent, interdisciplinary and interoperable cluster of Environmental Research Infrastructures across Europe. It is driven by three overarching goals: 1) promoting cross-fertilization between infrastructures, 2) implementing innovative concepts and devices across RIs, and 3) facilitating research and innovation in the field of environment for an increasing number of users outside the RIs.

ENVRIplus aligns its activities to a core strategic plan where sharing multi-disciplinary expertise will be most effective. The project aims to improve Earth observation monitoring systems and strategies, including actions to improve harmonization and innovation, and generate common solutions to many shared information technology and data related challenges. It also seeks to harmonize policies for access and provide strategies for knowledge transfer amongst RIs. ENVRIplus develops guidelines to enhance transdisciplinary use of data and data-products supported by applied use-cases involving RIs from different domains. The project coordinates actions to improve communication and cooperation, addressing Environmental RIs at all levels, from management to end-users, implementing RI-staff exchange programs, generating material for RI personnel, and proposing common strategic developments and actions for enhancing services to users and evaluating the socio-economic impacts.

ENVRIplus is expected to facilitate structuration and improve quality of services offered both within single RIs and at the pan-RI level. It promotes efficient and multi-disciplinary research offering new opportunities to users, new tools to RI managers and new communication strategies for environmental RI communities. The resulting solutions, services and other project outcomes are made available to all environmental RI initiatives, thus contributing to the development of a coherent European RI ecosystem.

TABLE OF CONTENTS

RESULTS AND RECCOMENDATION FROM THE COMPARISON EXERCISE OF SENSOR EMBEDDED PROCESSING PRACTICES

1. THE LOW-COST SENSORS REVOLUTION

With the evolution in the last years of programmable low-cost CPUs and microcontrollers (e.g.: Arduino, Raspberry Pi) it was experienced a blossoming in the market of low-cost sensors as well that could be embedded and managed with said platforms. These kinds of sensors cover a wide range of purposes from motion sensing, to cameras, to meteorological parameters up to monitoring airborne pollutants. The two latter areas become of particular interest for research fields such as precision agriculture and air quality research due to the possibility of deploying at an affordable cost a relatively dense network of sensors. While low-cost sensors are not expected to have the same performance as a high-cost analogue, their affordability allow them to be deployed in high numbers, therefore better characterizing certain phenomena that exhibit an high-degree of spatio-temporal variability. Air pollution monitoring is a prime example: reference instruments from local environmental protection agencies are extremely costly and, therefore, rarely more than three or four are deployed for a given municipality. While such locations are supposedly representative of the wider area it is quite possible that such sparse measurements are unable to capture certain sources or certain local effects that are distant from the measurement areas. Low-cost sensors, while not having the same absolute precision of reference instruments, can, instead, explore this unresolved spatial variability. This potentiality is attracting attention from all sides: market shares of these kind of sensors are increasing alongside the web-enabled microcontrollers/CPUs on which they are embedded (sharing, in this sense, the modern IoT revolution). Deployed sensor networks, enabling cities to better sense their environment and, eventually, respond to changes are a key infrastructure for the Smart Cities concept that MIT underlined as one of the 2018 ten breakthrough technologies. European Union is acknowledging low cost sensors networks with official publications (e.g.: Gerboles et al., 2017) as well as through project funding such as COST (e.g.: EuNetAir) or other actions (e.g.: EIP-SCC). All of this is of course intertwined with the growing scientific interests along these kind of technologies (e.g.: Castell et al., 2017), meaning a great relevance for all kind of research infrastructures working on sustainability, air pollution and atmospheric sciences. An example of such scientific preponderance is clearly visible by researching “low cost sensors network” in Web of Science: considering only results related to “air quality” (one of the most relevant scientific themes for these kinds of networks and the one on which CNR IBIMET/ANAEE has most experience) the research brings up 330 total results. Also, as it is clearly visible from figure 1, the scientific interest towards these kinds of sensors networks rose quickly in the past 4 years (2014-2018).

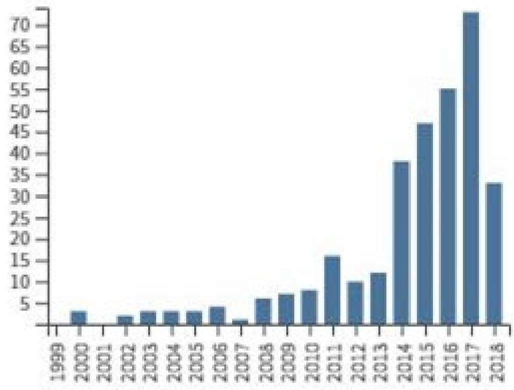

Figure 1: Thomson Reuter Web of Science Total Publications per Year on the topic "low cost sensors network" refined by topic "air quality".

While there is a certain "market explosion" for air quality sensors, in the case of the marine domain the market is still relatively small, even considering the Argo programme (~800 new floats a year worldwide). This issue may hinder the adoption of innovations, considering the investments required to evolve from a sensor to a smarter version. Embedded processing of sensor data therefore will likely take off mainly for sensors which produce large amounts of information that are too costly (in terms of economics and/or energy) to transmit over current data links. Sensor embedded processing is therefore still mainly driven by the need for data compression in specific scenarios, e.g. enabling the transmission of information via reduced amounts of data packets to users. A requirement for data transmission standards and lower influence of manufacturer specific interfaces to promote easier maintenance is playing also a large role such as in the case of EMSO Generic Instrumentation Module – EGIM – (Lanteri et al., 2017). Still, the scientific interest does not seem to be abated by this kind of market hindrances. Figure 2 shows that even for the marine domain the last 4 years received an increase in publications.

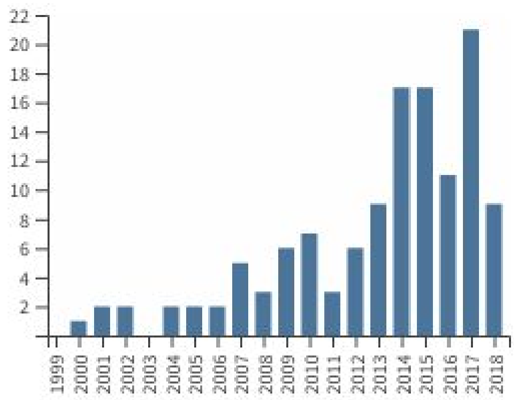

Figure 2: Thomson Reuter Web of Science Total Publications per Year on the topic “low cost sensors network” refined by topic “marine sensor”.

Given this kind of relevance for the scientific world and, therefore, for many research infrastructures, it is no surprising that part of the ENVRIPlus project is focused on recommendations regarding these kinds of sensors, especially due to the ever-growing scenarios of low-cost sensors producers and an ever-increasing difficulty in choosing a fitting sensor for the specific purpose at hand.

2. ANATOMY OF A LOW-COST SENSOR NETWORK

The deployment of a network of sensors generally follows the architecture detailed in figure 3. Multiple sensor nodes (which may consist of a single sensor monitoring a single variable or hubs of multiple sensors monitoring an array of variables) are distributed across the domain of interests. These nodes gather environmental data and relay them to a central database that is accessible to the end users (scientists, citizens, policy-makers, etcetera).

Sensor nodes can be either located in fixed positions (e.g.: David et al., 2016), either mounted on mobile platforms (such as cars, bikes, buses, etc., e.g.: Velasco et al., 2016), but they all rely the data to a central database/back-end system (e.g.: Mansour et al., 2014). This is true both for the atmospheric environment and for marine applications with the main differences consisting in the type of platforms employed. While atmospheric sensors might use land vehicles and small unmanned aerial vehicles (UAVs) as roving platforms, in the marine environment sensors would be deployed on stand-alone or cabled platforms, drifting floats (for both surface and water column) and autonomous underwater vehicles (AUVs).

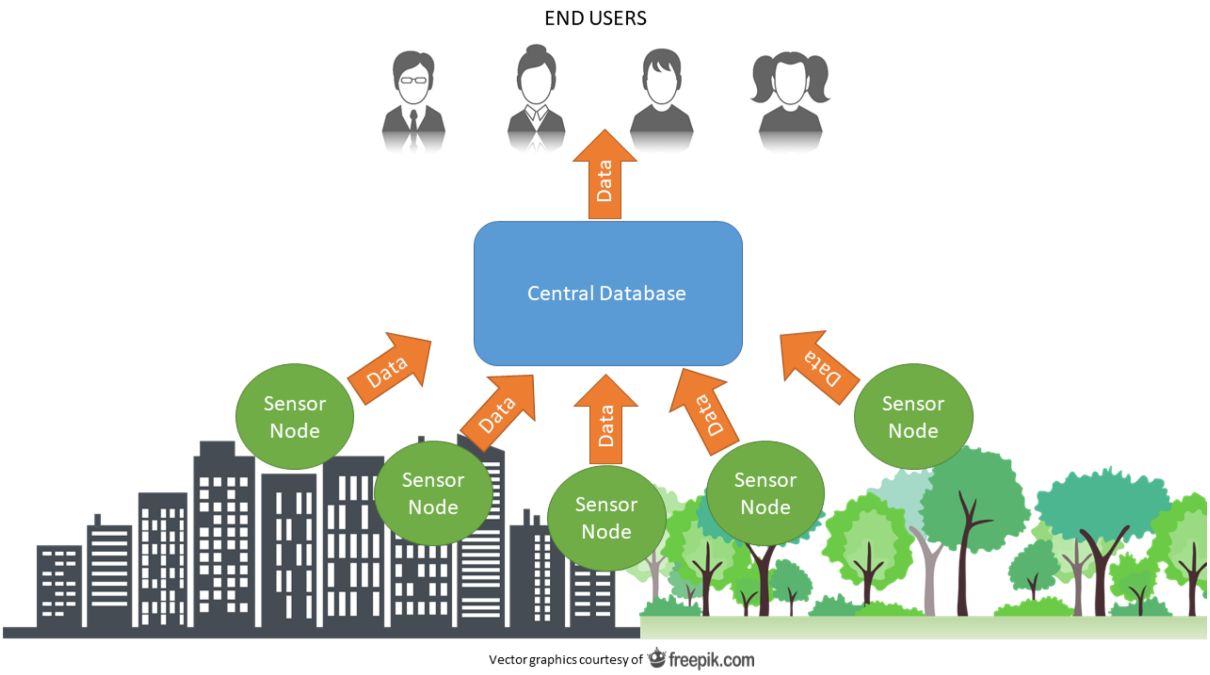

Figure 3: Typical configuration of a low-cost sensors network.

The general structure of a sensor node was well captured by Zhang et al. (2016) and re-presented here in figure 4

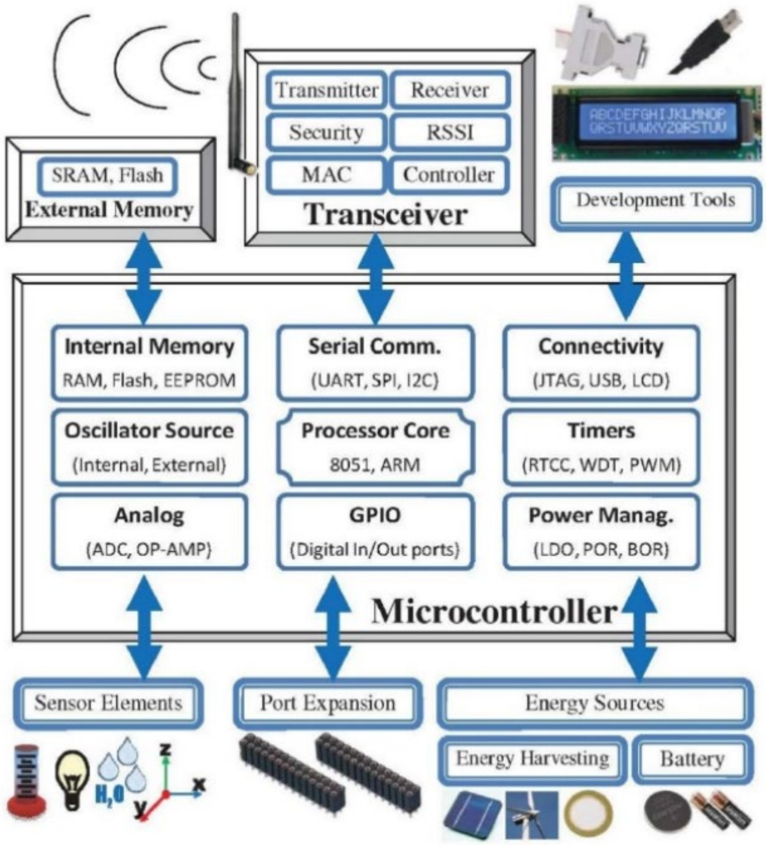

Figure 4: General structure of a wireless sensor network node, from Zhang et al. (2016)

The microcontroller unit (MCU) is the core of each sensor node acting as its "intelligence" and bridging the gap between the actual sensing elements, the communication portion of the node and the eventual onboard storage memory. The MCU is, in short, where embedded processing takes place. For the preparation of the present report more than 30 scientific papers and conference proceedings (see Supplementary Material 1: Wireless Sensor Network Literature) have been examined alongside with CNR IBIMET/ANAEE own experience. In most of the examined cases (94%) wireless sensor nodes made use of simple 8 or 16 bit microcontrollers (ARM, Intel, STMicroelectronics, Jennic, Texas Instrument were the main brands) and only in 6% of the cases more complex intelligences were employed (actual CPUs with embedded full-fledged operative systems). The MCU loop and, therefore, the embedded processes happening in different sensors nodes such as the IBIMET ones, the marine sensors from PLOCAN or Ifremer, or sensors from the literature, are actually very similar and follow the present scheme:

1. **Read sensors data.** The MCU acquires sensors data, generally voltages outputted by the sensors, and digitizes them with an onboard analog-to-digital (ADC) module. Specific sensors may need signal conditioning to output voltages readable by the MCU ADC module. This kind of conditioning is generally performed by dedicated circuit boards that are connected to the sensors on one side and to the MCU on the other (e.g.: Abraham & Li, 2016).

2. **Format sensors data.** the MCU passes the sensor data downstream eventually formatting them in some sort of data package. In case of the IBIMET experience, the onboard microcontroller, for example, generates a standard comma separated ASCII string. Currently being tested in marine systems, Sensor Web Enablement (OGC) may progressively harmonize this formatting layer to enable the transmission of data and metadata in an open standard fashion.

3. **Store/transmit sensors data.** The formatted data are either passed to some onboard memory (such an SD card or an EEPROM) either transmitted through a communication module that sends them through some kind of communication protocol. Sometimes these two processes may operate in parallel: in IBIMET experience, for example, the data string is both stored on an onboard memory, both sent to a centralized database through GPRS transmission. This ensures that data are not lost even in case of loss of connectivity. Open-ocean sensor systems generally transmit data via satellite links, deep stand-alone observatories also make use of acoustic modems with proprietary protocols before data can be air-transmitted to the data centers.

After a package has been sent, the MCU loops over, starting again from point 1). This might happen immediately or after some predetermined time has passed. The latter approach can be used to save battery power letting the system "sleep" between one acquisition and the other. This kind of approach has been used for example by Sanchez-Rosario et al. (2015): in their system each node was in sleep mode until a pre-programmed real-time clock (RTC) interrupt triggered data acquisition. Maraj et al. (2017) perform some simple computations on the Arduino MCU for their system in order to compute an air quality index. This is done in order to display it on an attached LCD display, but the latter is far from standard in a wireless sensor network (WSN). The main point of a WSN is, as the name implies, the transmission of the data and not the local display of it, therefore this embedded processing step is not considered in the comparison. In most of the analyzed systems the real intelligence is downstream, on the elaboration made on the data received by the central database. This makes sense: many of the WSN nodes may be deployed in mobile or remote environments where it is not possible to obtain continuous power from the grid. In Brienza et al. (2015) for example, the nodes are powered with 6600 mAh rechargeable batteries; in Velasquez et al. (2017), a 3.7 V, 2000 mAh battery recharged through a solar panel is used and batteries are employed also in Völgyesi et al. (2008); Zhang et al. (2016); Zheng et al. (2016) and many others systems. In short, sensor nodes are actually designed to *minimize* the amount of embedded processing beside physical boards for sensors signal conditioning and data transmission. In all the examined papers the embedded processing is very shortly detailed (if at all) since it follows a straightforward schematic for which the main differences are related to the programming language of the MCU: the two aspects of WSN on which literature (and IBIMET) display a great amount of effort and detail are **sensors calibration** and **communication protocols**. These are the two vital aspects of each WSN node since they are related to the quality of the transmitted data (calibration) and the ability of the sensor node to transmit data efficiently (communication protocols).

3. CNR IBIMET/ANAEE EXPERIENCE: THE AIRQINO WSN

The AIRQino sensor node, follows closely the schematics of fig. 3, with the main difference that there are two MCU layers: a PIC MCU board for sensor reading and signal digitization and an Arduino-compatible MCU (Seeduino Stalker V3) for the acquisition of the digitized signals and the wireless transmission via a GPRS shield. The AIRQino node in schematized in fig. 5.

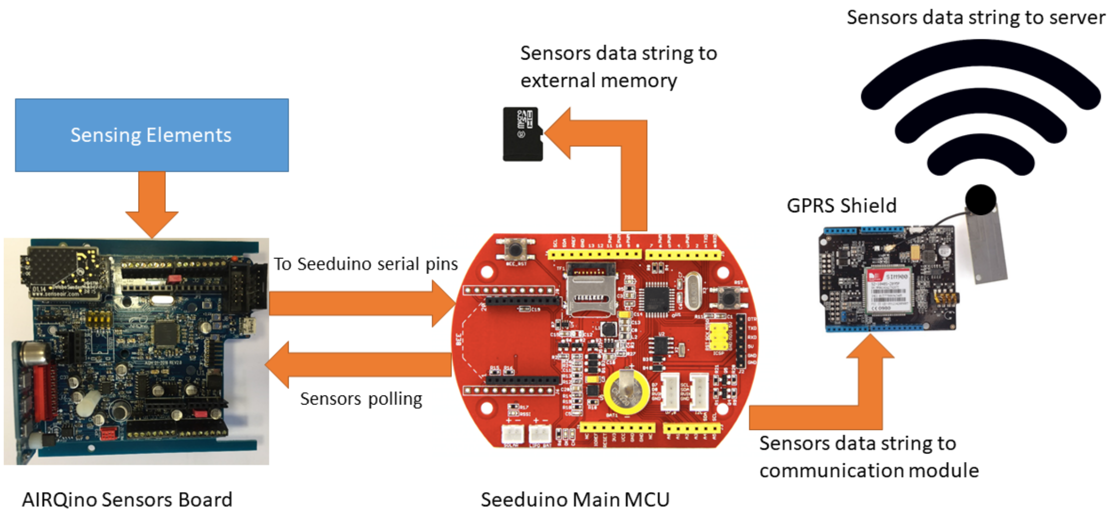

Figure 5: Schematics of CNR IBIMET/ANAEE AIRQino WSN Node

The sensing elements are installed on the AIRQino sensors board (ASB) which mounts a PIC-based MCU. The firmware of the MCU acquires the sensors voltages and digitizes them via an onboard ADC. The firmware acquires one sample per second and can be programmed to make a simple despiking via a 120-samples running average. The ASB is connected to the Tx and Rx serial pins of the main MCU. The latter uses these pins to poll the ASB and receive the digitized data in the form of an ASCII string. Polling interval is set at firmware level and can be configured via the standard Arduino IDE. The same firmware is responsible to invoke the GPRS shield to transmit the ASCII string to the IBIMET data server as well as saving it on an external memory. The latter operation is a backup solution to avoid losing data in case of GPRS signal loss. The system is powered via DC current: an internal DC-DC converter unit allows for a wide input range (10-30 Vdc) and the consumption is of 200mA (at 12Vdc and 2.5W). This set-up allows to power the AIRQino WSN node either via batteries or via regular power outlets (provided an AC-DC adapter is used) and makes it suitable for attachment, for example, to car or electric-bike batteries for mobile applications. The standard sensors array for the AIRQino system is detailed in the following table (table 1).

Parameter	**Unit**	**Sensor**	**Range**
Temperature	°C	AM2315	-40 – 80
Relative Humidity	%	AM2315	0 – 100
CO_2	ppm	SenseAir S8	0 – 2000
O_3	ppb	MQ-131	0 – 400
NO_2	ppm	MICS-2714	0.05 – 5
CO	ppm	MICS-5524	1 – 30
PM	µg m^{-3}	SDS011	0 – 999
VOC	ppm	MICS-5524	1 – 100

Table 1: AIRQino standard sensors array

The whole system is packaged in a rugged casing that allows it to withstand rainfall, dust, vibrations and even extreme conditions (AIRQino has been deployed in a long-term campaign on the Svalbard Islands). The casing is also made so that the airflow is optimized to minimize interferences and artifacts on the measurements of the sensors to the potential presence of interfering chemicals. Figure 6 shows some of the AIRQino deployments including the versions that have been specifically designed for airborne applications.

Figure 6: Some of the AIRQuino WSN node deployments in both fixed, mobile and extreme environments.

4. CALIBRATION: THE MAIN ISSUE WITH LOW-COST WSN

To put it in the words of Brienza et al. (2015): "*in order to obtain an acceptable accuracy each sensor node should be individually calibrated. The calibration phase is **often overlooked** in articles regarding sensor networks*" (boldface is from the authors). The main issue with low-cost WSN is not the on-board data processing, but rather obtaining accurate and sensible measurements with sensors that are just a fraction of the cost of the regular scientific sensors.

For the purpose of sensors calibration there are multiple techniques that can be applied to compare low-cost sensor outputs to one (or more) high-cost reference sensors.

- **Regression**: In the standard univariate linear regression (**LR**) the response of the low-cost and reference sensors are compared as a linear function of one another:

  $$y = mx + q \qquad (1)$$

  Where y are data from the reference sensors, x are data from the low-cost sensors and m and q are respectively the slope and the offset of the line best-fitting this set of (x,y) couples. In certain cases the reference sensors data are modeled not only after the correspondent low-cost sensors outputs, but as a linear combination of multiple variables. This is the so-called multivariate linear regression (**MLR**):

  $$y = m_1x_1 + m_2x_2 + m_3x_3 + \cdots + q \qquad (2)$$

  As an example the reference sensor NO_2 (y) could be modeled as a function of low-cost sensor NO_2 (m_1x_1), air temperature (m_2x_2) and relative humidity (m_3x_3). This allows to explain the reference sensors data variance with more variables that can be potentially acting on the concentration value. In certain cases it is possible to better fit low-cost sensors data to reference ones by expecting a nonlinear relationship between the two sensors. In the latter case it is a curve that better fits the couples of (x,y) points. Such kind of relationship are represented by higher degree formulas and can therefore be named nonlinear regressions (**NLR**). An example is the power relationship that can be described as:

$$y = mx^q \tag{3}$$

In which the high cost sensor data (y) are a nonlinear function of the low-cost ones (x).

Finally, all the presented regression methods are based on minimizing the sum of squared residuals in the modeled system (i.e.: least-squares method), but that method is based on the assumption that the independent variable (x) is measured without error as a design variable, while y is modeled as having an uncertainty or error. Since both can have an underpinning uncertainty, the least-squares assumptions can be violated. Methods such as the reduced major axis (**RMA**) regression can, instead, explicitly handle errors in both x and y variables.

- **Machine Learning**: Data analysis has been recently empowered by a series of machine learning (**ML**) models. Machine learning is a subset of the artificial intelligence topic and it focuses on "teaching" a computational device to predict outcomes on the basis of experience. Machine learning is closely related to computational statistics and mathematical optimization and it's based on algorithm that "learn" to make sense of input data. This might happen by training algorithms with a set of known "truths" that the algorithm may compare with its own predictions and consequently adjust (supervised learning) or leaving up to the algorithm the classification of the input data and, therefore, the ideation of a forecast model (unsupervised learning). These tasks may be accomplished with different approaches. It is out of the topic of this deliverable to give a comprehensive explanation of machine learning algorithms, but the most common approaches (that are found in the papers cited in Table 2) are briefly touched to give the reader a brief understanding of the following discussion about WSN calibration. Neural networks (**NN**) are a specific learning model. These networks have input nodes that receive the input data as-is and have the only use of passing them down to one or more layers of "neurons". In these layers the nodes (neurons) may perform different kind of transformation to the input signal and they pass it to connected neurons (connections are called "edges"). Edges have different weight associated to the input signals (which may also be 0, meaning that two neurons are essentially decoupled for that specific output) and these weights are adjusted through the learning process. Neural networks have finally an output layer that represents the exit from the system. Beside the input and the output layer the other ones are termed "hidden layers" since they represent essentially a black box regarding the processing of the data. In calibration terms it generally means that neural networks receive the data to calibrate as inputs (usually in a multivariate fashion) as well as the reference instruments data as correct outputs. The network then learns to derive correct data from the raw instrumental ones, generating a model that can, after its training, be applied to all the data outside the calibration set. A simpler ML algorithm compared to NN is the k-nearest neighbors one (**kNN**). As per NN, kNN can perform either regression or classification feats and it does so by taking a "vote" from a certain amount (k) of the nearest elements (NN) to the point that needs to be classified. kNN needs minimum learning, its non-parametric and works on the basis of feature similarity (the "vote" of the nearest neighbors). Finally, random forests (**RF**) are a method for ensemble learning that again can work for both classification and regression. The method performs a classification/regression on the basis of the modal outputs of a series of decision trees (a "forest").

Table 2 sums up all the examined literature on low-cost sensors calibration along with CNR IBIMET/ANEE own experience. The table reports the reference, the kind of calibrated pollutant, the used sensor, the type of calibration and the coefficient of correlation (r^2). The latter coefficient indicates the trend-wise agreement between the reference sensor and the low-cost sensor data after the application of the calibration model. This is the most important kind of agreement: while a difference in concentration magnitude can be generally an offset, a lack of agreement on the trend cannot be generally corrected in post processing.

Reference	**Pollution parameter**	**Sensor**	**Calibration**	R^2
Holstius et al., 2014	PM 2.5	PPD42	LR	≈ 0.5 - 0.7
Esposito et al., 2016	NO_2	NO2-B4	ML(NN)	≈ 0.6 - 0.8
Esposito et al., 2016	NOx	NO2-B4; NO-B4	ML(NN)	≈ 0.7 - 0.9
Esposito et al., 2016	O_3	O3-B4	ML(NN)	≈ 0.2 - 0.7
Spinelle et al., 2015	O_3	O3-B4	LR	< 0.1
Spinelle et al., 2015	O_3	O3-B4	MLR	≈ 0.5
Spinelle et al., 2015	O_3	O3-B4	ML(NN)	≈ 0.9
Spinelle et al., 2015	O_3	O3_3E1F	LR	≈ 0.8 - 0.9
Spinelle et al., 2015	O_3	O3_3E1F	MLR	≈ 0.8 - 0.9
Spinelle et al., 2015	O_3	O3_3E1F	ML(NN)	≈ 0.9
Spinelle et al., 2015	NO_2	CairClip NO2	LR	≈ 0.2 - 0.5

Spinelle et al., 2015	NO_2	CairClip NO2	MLR	≈ 0.6 - 0.7
Spinelle et al., 2015	NO_2	CairClip NO2	ML(NN)	≈ 0.5 - 0.6
Spinelle et al., 2015	NO_2	NO2-B4	LR	≈ 0.1 - 0.2
Spinelle et al., 2015	NO_2	NO2-B4	MLR	≈ 0.3 - 0.7
Spinelle et al., 2015	NO_2	NO2-B4	ML(NN)	≈ 0.5 - 0.6
Spinelle et al., 2015	NO_2	NO2_3E50	LR	< 0.1
Spinelle et al., 2015	NO_2	NO2_3E50	MLR	≈ 0.6 - 0.8
Spinelle et al., 2015	NO_2	NO2_3E50	ML(NN)	≈ 0.5 - 0.6
Spinelle et al., 2015	NO_2	MICS-2710	LR	≈ 0.2
Spinelle et al., 2015	NO_2	MICS-2710	MLR	≈ 0.7
Spinelle et al., 2015	NO_2	MICS-2710	ML(NN)	≈ 0.5 - 0.6
Spinelle et al., 2015	NO2	MICS-4514-NO2	LR	≈ 0.2 - 0.3
Spinelle et al., 2015	NO_2	MICS-4514-NO2	MLR	≈ 0.5 - 0.8
Spinelle et al., 2015	NO_2	MICS-4514-NO2	ML(NN)	≈ 0.5 - 0.6
Spinelle et al., 2015	NO_2	CairClip NO2	LR	≈ 0.2 - 0.5
Spinelle et al., 2015	NO_2	CairClip NO2	MLR	≈ 0.6 - 0.7
Spinelle et al., 2015	NO_2	CairClip NO2	ML(NN)	≈ 0.5 - 0.6
Spinelle et al., 2017	NO	NO_3E100	LR	<0.1
Spinelle et al., 2017	NO	NO_3E100	MLR	<0.1
Spinelle et al., 2017	NO	NO_3E100	ML(NN)	<0.1 - 0.2

Spinelle et al., 2017	CO	CO-TGS5042	LR	≈ 0.1
Spinelle et al., 2017	CO	CO-TGS5042	MLR	< 0.1
Spinelle et al., 2017	CO	CO-TGS5042	ML(NN)	≈ 0.3 - 0.4
Spinelle et al., 2017	CO	MICS-4514-CO	LR	≈ 0.8
Spinelle et al., 2017	CO	MICS-4514-CO	MLR	≈ 0.8
Spinelle et al., 2017	CO	MICS-4514-CO	ML(NN)	≈ 0.3 - 0.4
Spinelle et al., 2017	CO_2	S-100H-CO2	LR	≈ 0.1-0.9
Spinelle et al., 2017	CO_2	S-100H-CO2	MLR	≈ 0.8-0.9
Spinelle et al., 2017	CO_2	S-100H-CO2	ML(NN)	≈ 0.5 - 0.8
Spinelle et al., 2017	CO_2	CO2_GASCARD	LR	<0.1
Spinelle et al., 2017	CO_2	CO2_GASCARD	MLR	≈ 0.2
Spinelle et al., 2017	CO_2	CO2_GASCARD	ML(NN)	≈ 0.5 - 0.8
Hagan et al., 2018	SO_2	SO2-B4	LR	>0.9
Hagan et al., 2018	SO_2	SO2-B4	ML(kNN)	>0.9
Hagan et al., 2018	SO_2	SO2-B4	ML(LR+kNN)	>0.9
Wang et al., 2015	PM2.5	PPD42NS	LR	>0.9
Wang et al., 2015	PM2.5	PPD42NS	RMA	>0.9
Wang et al., 2015	PM2.5	DSM501A	LR	≈ 0.9
Wang et al., 2015	PM2.5	DSM501A	RMA	≈ 0.9
Wang et al., 2015	PM2.5	GP2Y1010AU0F	LR	>0.9

Wang et al., 2015	PM2.5	GP2Y1010AU0F	RMA	>0.9
Mijling et al., 2018	NO_2	NO2-B4	MLR	≈ 0.6 - 0.9
Zimmerman et al., 2018	CO	CO-B4	LR	≈ 0.8
Zimmerman et al., 2018	CO	CO-B4	MLR	≈ 0.8
Zimmerman et al., 2018	CO	CO-B4	ML(RF)	≈ 0.9
Zimmerman et al., 2018	CO_2	SST CO2S-A	LR	< 0.1
Zimmerman et al., 2018	CO_2	SST CO2S-A	MLR	≈ 0.1
Zimmerman et al., 2018	CO_2	SST CO2S-A	ML(RF)	≈ 0.7
Zimmerman et al., 2018	O_3	Ox-B4	LR	N/A
Zimmerman et al., 2018	O_3	Ox-B4	MLR	≈ 0.6
Zimmerman et al., 2018	O_3	Ox-B4	ML(RF)	≈ 0.9
Zimmerman et al., 2018	NO_2	NO2-B4	LR	≈ 0.4
Zimmerman et al., 2018	NO_2	NO2-B4	MLR	≈ 0.2
Zimmerman et al., 2018	NO_2	NO2-B4	ML(RF)	≈ 0.7
Borrego et al., 2016	PM10	PPD20V	LR	≈ 0.3
Borrego et al., 2016	PM10	CAIR	LR	≈ 0.1
Borrego et al., 2016	PM10	PPD42	LR	≈ 0.3
Borrego et al., 2016	PM2.5	CAIR	LR	<0.1
Borrego et al., 2016	PM2.5	PPD42	LR	≈ 0.2
Borrego et al., 2016	O_3	O3-B4	LR	≈ 0.1 - 0.7

Borrego et al., 2016	O_3	MICS-OZ-47	LR	≈ 0.8
Borrego et al., 2016	O_3	MICS-2610	LR	≈ 0.1
Borrego et al., 2016	SO_2	SO2-B4	LR	<0.1 - 0.2
Borrego et al., 2016	NO_2	NO2-B4	LR	<0.1 - 0.9
Borrego et al., 2016	NO_2	NO2_3E50	LR	0.9
Borrego et al., 2016	NO_2	MICS-2710	LR	<0.1
Borrego et al., 2016	CO	CO-B4	LR	≈ 0.5 - 0.9
Borrego et al., 2016	NO	NO-B4	LR	≈ 0.3 - 0.8
Jiao et al., 2016	PMx	PM-SYS-1	LR	≈ 0.4
Jiao et al., 2016	PMx	PM-SYS-1	MLR	≈ 0.4
Jiao et al., 2016	PMx	DC1100	LR	≈ 0.3 -0.4
Jiao et al., 2016	PMx	DC1100	MLR	≈ 0.4 - 0.6
Jiao et al., 2016	PMx	PPD60PV	LR	≈ 0.4
Jiao et al., 2016	PMx	PPD60PV	MLR	≈ 0.4 - 0.5
Jiao et al., 2016	O_3	Aeroqual SM50	LR	≈ 0.8 - 0.9
Jiao et al., 2016	O_3	Aeroqual SM50	MLR	≈ 0.9
Jiao et al., 2016	O_3	Cairclip-O3	LR	≈ 0.7 - 0.9
Jiao et al., 2016	O_3	Cairclip-O3	MLR	≈ 0.9 - > 0.9
Jiao et al., 2016	NO_2	Cairclip-NO2	LR	≈ 0.6
Jiao et al., 2016	NO_2	Cairclip-NO2	MLR	≈ 0.6 - 0.8

Jiao et al., 2016	NO	AQMesh	LR	≈ 0.8 - 0.9
Jiao et al., 2016	NO	AQMesh	MLR	≈ 0.7 - 0.8
Jiao et al., 2016	CO	AQmesh	LR	≈ 0.6 - 0.7
Jiao et al., 2016	CO	AQmesh	MLR	≈ 0.6 - 0.7
Castell et al., 2017	CO	AQmesh	LR	≈ 0.3
Castell et al., 2017	NO	AQmesh	LR	≈ 0.9
Castell et al., 2017	NO_2	AQmesh	LR	<0.1 - 0.4
Castell et al., 2017	O_3	AQmesh	LR	<0.1 - 0.7
IBIMET	O_3	MQ-131	NLR	≈ 0.6 - 0.9
IBIMET	NO_2	MICS-2714	NLR	≈ 0.5 - 0.7
IBIMET	CO	MICS-5524	NLR	≈ 0.2 - 0.5
IBIMET	PM2.5	SDS011	NLR	≈ 0.5 - 0.9
IBIMET	PM10	SDS011	NLR	≈ 0.3 - 0.8

Table 2: Calibration data for different pollution parameters, sensors and calibration methods.

There are several important messages and caveats that RIs can derive from the apparently simple Table 2 of the present deliverable.

1. First and foremost is that more complex calibration methods are not mandatorily better than simpler ones. In Spinelle et al. (2017), for example, the CO-B4 sensors returned a correlation coefficient of roughly 0.8 for both LR and MLR, while the machine learning methods achieved coefficients that are not greater than 0.4.

2. The benefits of employing a MLR calibration strongly depends by the feasibility of always having the full set of variables and to have them validated. This might not always be the case when deploying a certain subset of sensors also because it is not known a priori what would be the most significant variables co-varying with the pollution parameter to be calibrated. While on one hand a certain sensor could benefit from MLR as, for example, the O3-B4 in Spinelle et al. (2017) (r^2 rose from <0.1 up to 0.5 when switching from LR to

MLR); in certain cases it could **worsen** the calibration. An example of the latter is NO2-B4 in Zimmerman et al. (2018) where LR returned an r^2 of 0.4, while MLR of 0.2.

3. Sensors themselves have a strong impact. Different sensors measuring CO, for example, yielded widely different results when calibrated with LR. CO-B4 returned an r^2 of 0.8 (Zimmermann et al., 2018); CO-TGS5042 one of roughly 0.1 (Spinelle et al., 2017); MICS-454-CO one of 0.8 (Spinelle et al., 2017) and, finally, MICS-5524 one between 0.2 and 0.5 (IBIMET). Choosing a sensor brand that obtains good results in literature is also not a complete guarantee of good results. Sensor batches might have quite different sensitivities and performances. This have been seen by IBIMET and by, for example, Borrego et al. (2016) where the same NO2-B4 sensors yielded r^2 ranging between <0.1 (almost no agreement with references) up to 0.9 (almost perfect agreement with references).

4. Reactive pollutants complicate greatly environmental calibrations. Substances such as O_3 and NOx are photochemically active, while CO_2 may have interactions with environmental relative humidity. This may explain poor performances of simple calibration methods on these pollutants (e.g.: Zimmerman et al., 2018; Spinelle et al., 2017). For these pollution parameters a multivariate or more complicated approach might be necessary for appropriate calibration. Even in this case the caveats about MLR of point 2 still apply: for NO2-B4 even a MLR approach yielded only a r^2 of 0.2, and only ML algorithm could increase this relationship up to 0.7 (Zimmerman et al., 2018).

5. Linearity of the response is not always guaranteed. One of the reasons for which LR may yield poor results is that, compared with scientific-grade high cost instruments, low cost sensors may not respond linearly to the increase in pollution parameters. This has been seen by IBIMET and integrated in its calibration approach which explores different NLR regression methods.

On the basis of this analysis any RI that's interested in using low cost sensors should pay particular attention to the calibration of the individual sensors and avoid as much as possible the usage of common coefficients/models based on the testing of only a batch of sensors in the network. It must be paid particular attention to the sensors measuring reactive pollutants and to the effective linearity of the response. The suggestion is to employ univariate LR and NLR methods as a first calibration instance and move to MLR and ML methods only if the full set of variables that will be used as an input to these methods can be obtained consistently across the network of sensors and can be validated on its own.

5. COMMUNICATIONS: ALTERNATIVE APPROACHES

5.1 LoRa WAN and SIGFOX

One of the take-away messages from paragraph 2 is that the main issues with WSN are not related to embedded processing practices but rather to calibration and communication issues. IBIMET main approach with AIRQino boards is to transmit data via a GPRS, which is feasible since main deployments are in urban areas with good cellular coverage. This is not true for WSN that are applied in more remote areas such as the precision agriculture version of the AIRQino node (the AgroDuino node) where coverage is not available. In rural areas signal coverage might not be the only problem, but also power availability. More often this means that WSN nodes must rely on battery power rather than continuous sources: squeezing out more efficiency from the communication protocol becomes of paramount importance to avoid draining the batteries in a short amount of time. Also, the WSN nodes generally need to transmit small packages (often strings or even binary data) for which GPRS protocol specification are oversized in terms of bandwidth and speed of communications. Employing GPRS also means the need to pay a monthly fee to a phone operator which not only can be a significant cost depending on the number of nodes, but also a significant drawback if sensors must be shared between RIs and located in different countries with different operators. Another limitation comes for the tracking of extreme phenomena such as water pollution during storms (Jerico RI in coastal zone for instance) or unstable slopes or volcanology (EMSO RI) the public GPRS network is liable to stop working during the targeted event.

A solution to this problem could come from Low-Power Wide-Area Networks (LPWAN), allowing long-range, low-bitrate communications between connected devices and to be an alternative to GPRS systems for machine-to-machine (M2M) communications. These kinds of networks generally operate at 100 bps and are extremely conservatives in terms of power, requiring only 2.5 Watt of current. Beecham Research foresees that by 2020 LPWAN networks will cover 26% of the global IoT connectivity market, with 345 million of connections. An alternative approach to LPWAN is the ZigBee proprietary protocol, but, beside being fully proprietary it does not yield the same efficiencies in terms of range and power consumption (an overview of the different communication protocol is visible in figure 7).

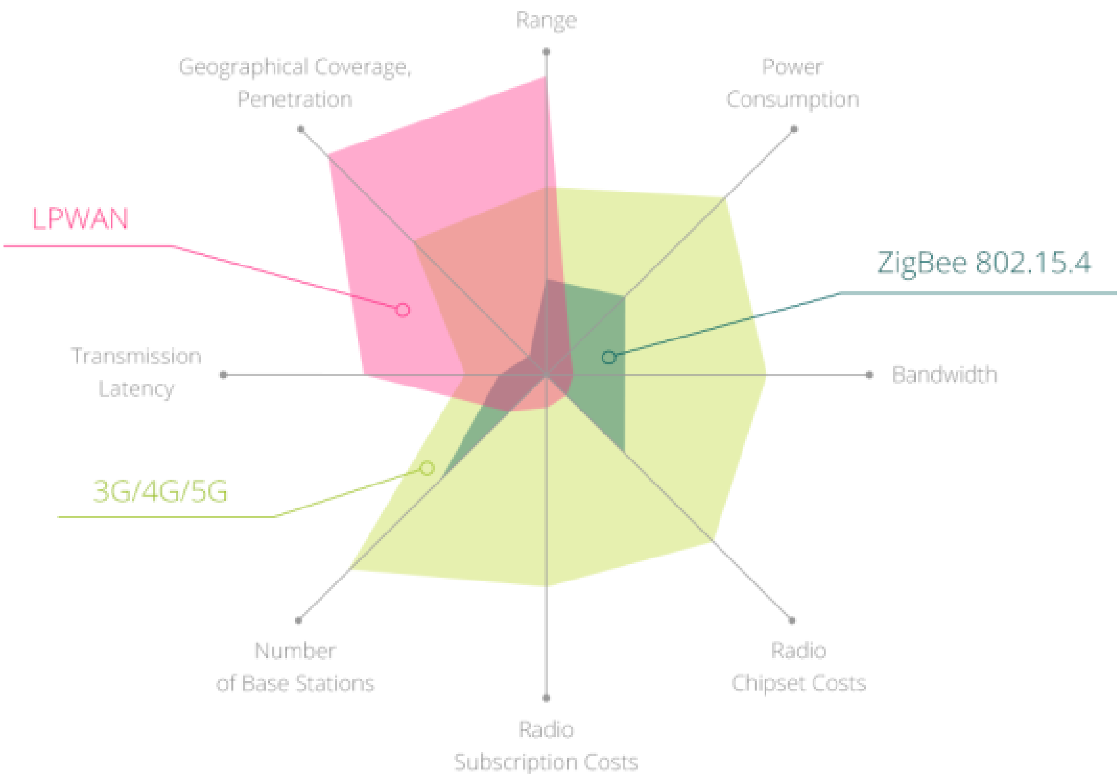

Figure 7: Comparison of the various communication protocols

Of course, LPWAN carriers are not the cellular ones and, in fact, there are two main technological approaches: chirp spread spectrum (CSS) for which LoRa (Cycleo, Grenoble, France, then acquired by Semtech) is the main commercial product and ultra narrow band (UNB) for which SigFox is the main commercial product.

CSS employs wideband linear frequency modulated chirp pulses to encode information. This makes it resistant to multi-path fading and Doppler effect. LoRa in specific uses license-free sub-GHz radio frequency bands. The LoRa signal has up to 15 km range in open field and can encrypt data with AES-128 making communications secure. LoRa uses a market approach of free-software but closed-hardware: software is open and anyone can freely use it by joining the LoRa Alliance, but transmission systems are only produced by Semtech. The typical architecture of a LoRa network is presented in figure 8.

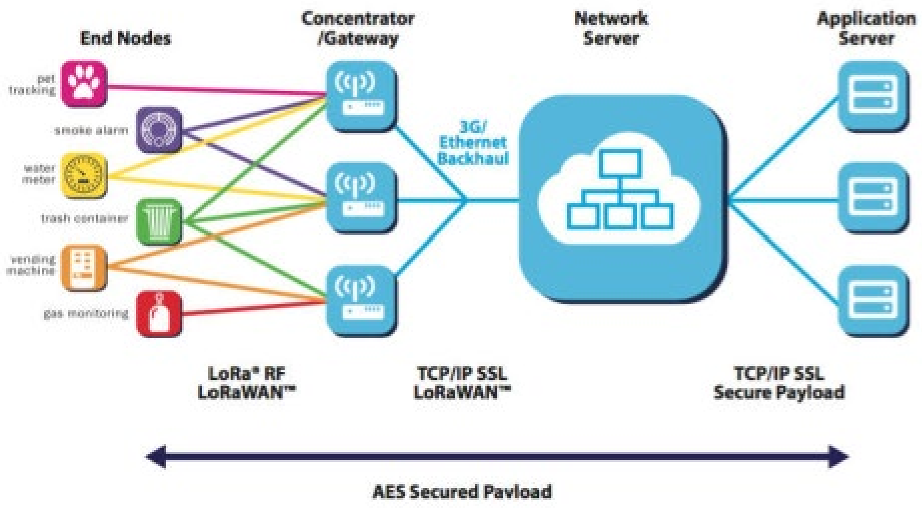

Figure 8: LoRa typical architecture.

As it is possible to see from figure 6, LoRa nodes transmit data to a concentrator/gateway that needs a TCP/IP enabled protocol to finally relay data over-IP to a database/server. This means that only the concentrator (or concentrators in case of wide networks) require GPRS coverage and subscription, while all the nodes transmit data over LoRa with a low power consumption and no subscription fees.

UNB technology focuses, instead, on a very narrow spectrum channel as the carrier. SigFox is one of the main players for UNB LPWAN and has a good coverage across Europe since every country has its own local SigFox operator managing the local infrastructure. The marketing strategy of SigFox is the opposite of LoRa: there is no proprietary encoding for data transmission and therefore anyone can build a SigFox transmitter/receiver, but a subscription is needed to transmit packages over SigFox. The SigFox infrastructure then takes care of over-IP secure transmission of packages to the end-user infrastructure (data server etcetera, see figure 9).

Figure 9: SigFox infrastructure

The overall performances of the systems are comparable and therefore the choice generally depends on the amount of information that needs to be sent: if packages are sparse enough an RI could choose to invest in a moderate subscription and cheaper hardware, if the amount of packages increases the LoRa approach is more efficient.

For AgroDuino (figure 10) IBIMET chose SigFox due to the low amount of sent packages. The main difference with the AIRQino board is the usage of a SigFox instead than of a GPRS shield for data transmission as well as sensors for soil humidity and temperature instead than airborne pollutants. Finally, the other significant differences are the usage in the MCU programming of the "LowPower" library and the casting of the data-type.

Data casting reduces the size of the transmitted packages by forcing the data acquired from the sensors to the smallest possible data-type for the acquired values (e.g.: battery voltage is first converted to a value ranging between 0 and 255 and then casted as unsigned char).

After each transmission through the SigFox shield the LowPower library switches the MCU to a sleep mode until the next acquisition/sending cycle. Considering only the MCU absorption this would yield up to 28 days of continuous operation with a data package sent every 15 minutes on a single battery charge (12V, 7.2 Ah battery).

The addition of a solar panel to the AgroDuino set-up combined with such a low-power operation makes the WSN node energy independent even in a situation where no continuous sources of power are available.

Figure 10: an AgroDuino WSN node deployed in a vineyard

5.2 THE PLOCAN EXPERIENCE - SIGNAL PREPROCESSING IN THE MARINE ENVIRONMENT

The interest in monitoring underwater sound has raised in European marine RIs with the European Marine Strategy Framework Directive (MSFD) Descriptor 11. Open-ocean monitoring of underwater sound for environmental purposes (ambient noise levels) implies the use of specialised high-sensitivity equipment: low-noise preamplified calibrated hydrophone (ideally reference hydrophones for their high sensitivity), a high sampling rate high resolution data acquisition system. Raw data production rates thus can routinely reach Megabits per second (Mbps), and terabytes per year when storing/archiving raw data - whenever desirable. Real-time transmission in an open-ocean context is thus still prohibitive in most cases - although costs will reduce the improvement of RF links, whether satellite or shore-based.
The alternative communication approaches described in the previous paragraph (5.1) are not suitable for such extreme environments and for the amount of data that hydrophone generates, and, therefore, signal pre-processing routines are necessary to reduce the amount of data to manageable size.

Preprocessing acoustic data in the marine domain is now at reach for ocean observing systems thanks to the use of low-cost CPUs and the work performed by the PAM community of algorithm and open-source software developers. Optimised versions of the codes can be ported to low-power systems.

Embedded acoustic processing on-board deep vehicles has reached a level of development that will soon become routine. Fig 10-15 illustrate the recent integration on board floats and gliders, with real data acquired and transmitted of sound statistics near real-time to shore (at every surfacing phase). Several functionalities were ported to the sensor processing unit, including MSFD indicators for Descriptor 11 (third octave and broadband) and bioacoustics (Toma *et al.* 2018, Delory *et al.* 2019). Open hardware also allowed the addition of other routines by users as the linux-based firmware can be modified.

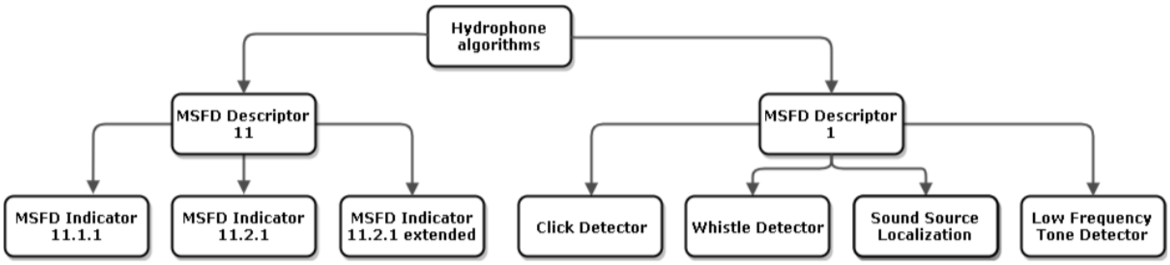

Fig.10 MSFD indicators covered by the algorithms implemented in A1 hydrophone. See (Toma et al. 2018), where the implementation of all algorithms is described.

Fig 11. Passive Acoustic Monitoring (PAM) system attached to a Liquid Robotics SV2 wave glider at PLOCAN (EnvriPLUS-MARCET mission, August 2018).

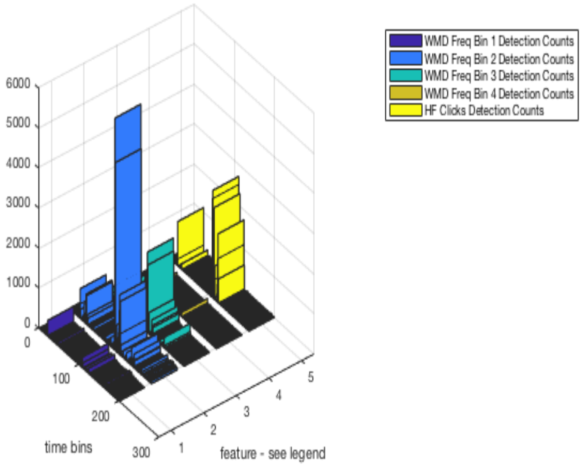

Fig.12 Whistle and click detection counts off Gran Canaria resulting from embedded acoustic processing, transmitted real-time, while acoustic raw data is stored on-board for further processing after system recovery (EnvriPLUS-MARCET, August 2018)

Fig.13 (left) Argo float (NKE PROVOR) with hydrophone (black sensor, top of the float) NeXOS A1, embedding acoustic processing for MSFD descriptor 11. (right) Integration on deep glider (Sea Explorer, Courtesy of NeXOS and Alseamar).

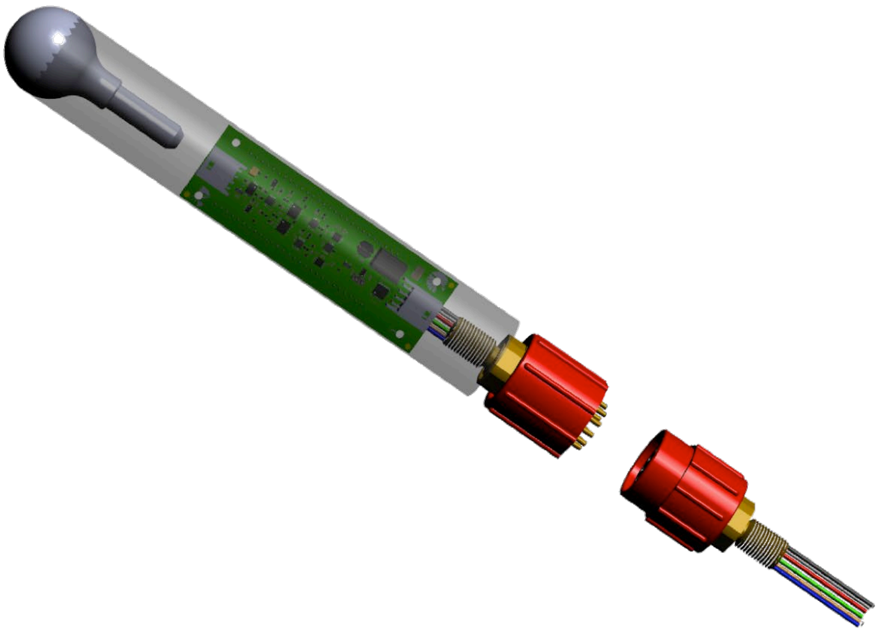

Fig.14 Rendering of hydrophone NeXOS A1 with preprocessing stage based on an ARM processor (Courtesy: Developers: PLOCAN-UPC-SITEP)

Fig.15 Deep glider (Alseamar Sea Explorer) equipped with NeXOS A1 and near real-time transmission of processed data (third octave band centered at 125Hz) off the Norwegian sea

In such marine applications, the sensor interface is crucial. It must include digital conversion and sensor embedded pre processing based on calibration parameters. Another type of preprocessing function is the generation of alerts when a set of parameters reaches a threshold. It is under

development for water quality in estuaries and coastal areas (JERICO RI) and implemented on some EMSO sites (seismic events on EMSO Azores for instance – Cannat et al., 2016).
For EMSO Generic Instrumentation module, a new development has been necessary to base the data collection of several sensors dealing with different parameters (up to 12) on very low power consumption electronics (Lanteri et al., 2017). The above mentioned A1 hydrophone is based on an innovative design with a newly developed electronic board too.

To be able to compare results, standards of data formats are necessary. This data interface topic going as far as sensor web enablement is addressed in ENVRIPlus WP3 (see Deliverable D3.3 "Report for best practices on robust telecom/datatransmission » - Huber et al.).

6. CONCLUSIONS

The present deliverable sums up all the recommendations that can be provided to RIs facing the challenge of deploying WSNs. The deliverable combined an extensive comparison of literature data with the IBIMET experience with WSNs matured in 36 months of ENVRIPlus project. After careful consideration it is possible to conclude that embedded processing is not the real issue with WSNs. Due to power and communication restrictions, the best option is, in fact, to minimize the amount of processing that happens on a WSN node (which generally operates with relatively simple MCUs). In all the surveyed literature the embedded processing followed a simple repeated scheme: read data from sensors, format them for transmission and send them to a central database where more complex elaboration could happen without taking the toll on the WSN node battery power. The simple embedded operations that are involved in this cycle are straightforward and are limit to data casting, running averages and, eventually, the application of simple formulas to calculate indexes from read data (Maraj et al., 2017). The criticalities on which both literature data and IBIMET experience converged where on the quality of the acquired data and on the restriction on the communication protocols. The former strongly depends on the correct calibration of the sensors for which careful considerations should be made in comparison to high-cost sensors: for low-cost sensors linearity of response is not guaranteed and the difference in response between sensors of the same batch might be significant. The caveat for RIs is therefore to individually calibrate each sensor employed with both linear and non-linear regression methods. Finally, WSN node may be deployed in places where there's no WI-FI, LAN or GPRS coverage and where access to continuous power is limited or non-existent. For the latter case the suggestion is to employ LPWAN communication approaches on the WSN sensors nodes and add sleep instructions between each acquisition cycles in order to maximize the field life of the WSN node and its energy independence. These solutions are not applicable in remote applications in the marine environment, where the set-up of these kinds of networks is unfeasible not only due to the complexity of the environment but also due to the amount of data generated by the sensors. Due to this data transmission/storage issues in the marine domain it would be advisable to empower the MCU with either hardware or software signal processing routines in order to have data sizes that are manageable for the marine WSNs. The type of platforms has driven the requirements for sensor design and, due to their limited autonomy and communication bandwidth, the advent of AUVs in monitoring the ocean is undoubtedly the main driver for embedded processing of sensor data. Innovations targeting AUVs will in turn also benefit other less constraining platforms, allowing for the deployment of more sensors and lower the cost of procurement due to the increasing market opportunities. Still, practices of embedded processing in marine applications for environmental purposes are only emerging.

7. REFERENCES

Abraham, S., & Li, X. (2016). Design of A Low-Cost Wireless Indoor Air Quality Sensor Network System. International Journal of Wireless Information Networks, 23(1), 57–65. https://doi.org/10.1007/s10776-016-0299-y

Borrego, C., Costa, A. M., Ginja, J., Amorim, M., Coutinho, M., Karatzas, K., Sioumis, T., Katsifarakis, N., Konstantinidis, K., De Vito, S., Esposito, E., Smith, P., André, N., Gérard, P., Francis, L., Castell, N., Schneider, P., Viana, M., Minguillón, M., Reimringer, W., Otjes, R., von Sicard, O., Pohle, R., Elen, B., Suriano, D., Pfister, V., Dipinto, S., Penza, M. (2016). Assessment of air quality microsensors versus reference methods: The EuNetAir joint exercise. Atmospheric Environment, 147, 246–263. https://doi.org/10.1016/j.atmosenv.2016.09.050

Brienza, S., Galli, A., Anastasi, G., & Bruschi, P. (2015). A low-cost sensing system for cooperative air quality monitoring in urban areas. Sensors (Switzerland), 15(6), 12242–12259. https://doi.org/10.3390/s150612242

Cannat M., Sarradin P.-M., Blandin J., Ballu V., Barreyre T., Chavagnac V., Colaco A., Crawford W., Daniel R., Escartin J., Legrand J., Matabos M., Rommevaux C., Roullet G., Reverdin G., Sarrazin J. (2016). EMSO-Azores : Monitoring seafloor and water column processes at the Mid-Atlantic Ridge. *Fix03 - Project Newsletter. Service Activities Special*, 3(1), 11. Open Access version : https://archimer.ifremer.fr/doc/00353/46444/

Castell, N., Dauge, F. R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., Bartonova, A. (2017). Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? Environment International, 99, 293–302. https://doi.org/10.1016/j.envint.2016.12.007

David, C. M., River, Q. T., Jorge, R. M., Andres, J. K., & Guillermo, G. L. (2016). A low-cost, rapid-deployment and energy-autonomous wireless sensor network for air quality monitoring. In Proceedings of the International Conference on Sensing Technology, ICST (Vol. 2016–March, pp. 122–127). IEEE. https://doi.org/10.1109/ICSensT.2015.7438376

Delory, E., Toma, D. M., Del Rio, F. J., Cervantes, P., Ruiz, P., & Memè, S. (2019). A New Generation of Interoperable Oceanic Passive Acoustics Sensors With Embedded Processing. In Cambridge: Elsevier (Ed.), Challenges and Innovations in Ocean In Situ Sensors (pp. 117–134).

Esposito, E., De Vito, S., Salvato, M., Bright, V., Jones, R. L., & Popoola, O. (2016). Dynamic neural network architectures for on field stochastic calibration of indicative low cost air quality sensing systems. Sensors and Actuators, B: Chemical, 231, 701–713. https://doi.org/10.1016/j.snb.2016.03.038

Hagan, D. H., Isaacman-Vanwertz, G., Franklin, J. P., Wallace, L. M. M., Kocar, B. D., Heald, C. L., & Kroll, J. H. (2018). Calibration and assessment of electrochemical air quality sensors by co-location with regulatory-grade instruments. Atmospheric Measurement Techniques, 11(1), 315–328. https://doi.org/10.5194/amt-11-315-2018

Holstius, D. M., Pillarisetti, A., Smith, K. R., & Seto, E. (2014). Field calibrations of a low-cost aerosol sensor at a regulatory monitoring site in California. Atmospheric Measurement Techniques, 7(4), 1121–1131. https://doi.org/10.5194/amt-7-1121-2014

Huber, R., Gilbert, O., Vermeulen, A., Papale, D., Rolin, J.-F., Waldmann, C., Rohs, S., (2017). Report for best practices on robust telecom/datatransmission. ENVRIPLUS Deliverable D3.3.- http://www.envriplus.eu/wp-content/uploads/2015/08/D3.3.pdf

Jiao, W., Hagler, G., Williams, R., Sharpe, R., Brown, R., Garver, D., Judge, R., Caudill, M., Rickard, J., Davis, M., Weinstock, L., Zimmer-Dauphinee, S., Buckley, K. (2016). Community Air Sensor Network (CAIRSENSE) project: Evaluation of low-cost sensor performance in a suburban environment in the southeastern United States. Atmospheric Measurement Techniques, 9(11), 5281–5292. https://doi.org/10.5194/amt-9-5281-2016

Lanteri, N., Legrand, J., Moreau, B., Lagadec J.-R., Rolin J.-F. (2017). The EGIM, a generic instrumental module to equip EMSO observatories. In OCEAN 2017 –Aberdeen .IEEE. Pages 1-5. http://dx.doi.org/10.1109/OCEANSE.2017.8084824

Mansour, S., Nasser, N., Karim, L., & Ali, A. (2014). Wireless sensor network-based air quality monitoring system. In 2014 International Conference on Computing, Networking and Communications, ICNC 2014 (pp. 545–550). IEEE. https://doi.org/10.1109/ICCNC.2014.6785394

Maraj, A., Berzati, S., Efendiu, I., Shala, A., Dermaku, J., & Melekoglu, E. (2017). Sensing platform development for air quality measurements and analysis. In South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2017,1-5. IEEE. https://doi.org/10.23919/SEEDA-CECNSM.2017.8088233

Mijling, B., Jiang, Q., de Jonge, D., & Bocconi, S. (2018). Field calibration of electrochemical NO2 sensors in a citizen science context. Atmospheric Measurement Techniques, 11(3), 1297–1312. https://doi.org/10.5194/amt-11-1297-2018

Sanchez-Rosario, F., Sanchez-Rodriguez, D., Alonso-Hernandez, J. B., Travieso-Gonzalez, C. M., Alonso-Gonzalez, I., Ley-Bosch, C., Ramirez-Casanas, C., Quintana-Suarez, M. A. (2015). A low consumption real time environmental monitoring system for smart cities based on ZigBee wireless sensor network. In IWCMC 2015 - 11th International Wireless Communications and Mobile Computing Conference (pp. 702–707). IEEE. https://doi.org/10.1109/IWCMC.2015.7289169

Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M., & Bonavitacola, F. (2015). Field calibration of a cluster of low-cost available sensors for air quality monitoring. Part A: Ozone and nitrogen dioxide. In Sensors and Actuators, B: Chemical (Vol. 215, pp. 249–257). https://doi.org/10.1016/j.snb.2015.03.031

Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M., & Bonavitacola, F. (2017). Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2. Sensors and Actuators, B: Chemical, 238, 706–715. https://doi.org/10.1016/j.snb.2016.07.036

Toma, D. M., Masmitja, I., del Río, F. J., Martinez, E., Artero-Delgado, C., Casale, A., Figoli, A., Pinzani, D., Cervantes, P., Ruiz, P., Memè, S., Delory, E. (2018). Smart embedded passive acoustic devices for real-time hydroacoustic surveys. Measurement: Journal of the International Measurement Confederation,125,592-605, https://doi.org/10.1016/j.measurement.2018.05.030

Velasco, A., Ferrero, R., Gandino, F., Montrucchio, B., & Rebaudengo, M. (2016). A mobile and low-cost system for environmental monitoring: A case study. Sensors (Switzerland), 16(5), 710. https://doi.org/10.3390/s16050710

Velásquez, P., Vásquez, L., Correa, C., & Rivera, D. (2017). A low-cost IoT based environmental monitoring system. A citizen approach to pollution awareness. In 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies, CHILECON 2017 - Proceedings (Vol. 2017–Janua, pp. 1–6). IEEE. https://doi.org/10.1109/CHILECON.2017.8229599

Völgyesi, P., Nádas, A., Koutsoukos, X., & Lédeczi, Á. (2008). Air quality monitoring with SensorMap. In Proceedings - 2008 International Conference on Information Processing in Sensor Networks, IPSN 2008 (pp. 529–530). IEEE. https://doi.org/10.1109/IPSN.2008.50

Wang, Y., Li, J., Jing, H., Zhang, Q., Jiang, J., & Biswas, P. (2015). Laboratory Evaluation and Calibration of Three Low-Cost Particle Sensors for Particulate Matter Measurement. Aerosol Science and Technology, 49(11), 1063–1077. https://doi.org/10.1080/02786826.2015.1100710

Zhang, X., Zhao, Y., Zhao, W., Xu, W., & Ji, W. (2016). A Wireless Sensor Networks-based Intelligent System for Library Air Quality Monitoring. International Journal of Online Engineering (IJOE), 12(11), 76. https://doi.org/10.3991/ijoe.v12i11.6227

Zheng, K., Zhao, S., Yang, Z., Xiong, X., & Xiang, W. (2016). Design and Implementation of LPWA-Based Air Quality Monitoring System. IEEE Access, 4, 3238–3245. https://doi.org/10.1109/ACCESS.2016.2582153

Zimmerman, N., Presto, A. A., Kumar, S. P. N., Gu, J., Hauryliuk, A., Robinson, E. S., & Robinson, A. L. (2018). A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. Atmospheric Measurement Techniques, 11(1), 291–313. https://doi.org/10.5194/amt-11-291-2018