Calibrating Low-Cost Air Quality Sensors Using Multiple Arrays of Sensors

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***Abstract*—The remarkable advances in sensing and communication technologies have introduced increasingly low-cost, smart and portable sensors that can be embedded everywhere and play an important role in environmental sensing applications such as air quality monitoring. These user-friendly wireless sensor platforms enable assessment of human exposure to air pollution through observations at high spatial resolution in near-real-time, thus providing new opportunities to simultaneously enhance existing monitoring systems, as well as engage citizens in active environmental monitoring. However, data quality from such platforms is a concern since sensing hardware of such devices is generally characterized by a reduced accuracy, precision, and reliability. Achieving good data quality and maintaining error free measurements during the whole system lifetime is challenging. Over time, sensors become subject to several sources of unknown and uncontrollable faulty data which comprise the accuracy of the measurements and yield observations far from the expected values. This paper investigates calibration of low-cost air quality sensors in a real sensor network deployment. The approach leverages on the availability of sensor arrays in a wireless node to estimate parameters that minimize the calibration error using fusion of data from multiple sensors. The obtained results were encouraging and show the effectiveness of the approach compared to a single sensor calibration.**

***Index Terms*—Sensor networks, Ozone sensors, Calibration; Data fusion; Array of sensors; Multivariate estimation.**

I. Introduction

Nowadays, urban air quality represents a major concern to the environment, the public health, and ultimately, the economy of all countries as air pollution impairs citizens health and quality of life. Currently air pollution concentrations are monitored using static monitoring stations equipped with certified reference instruments which are relatively large, heavy and expensive. With the growing progress in sensor technology, many sensor manufacturers are selling low-cost sensors with a wide range of sensing applications such as air pollution. This unique class of air monitoring sensor devices such as O_3, CO, NO_x, CO_2, etc. when integrated into a wireless sensor network (WSN) provides for continuous air quality measurements and for more ubiquitous pollutant monitoring systems. Sensor nodes can be deployed as dense networks or mounted on vehicles, facilitating the elaboration of high-resolution air quality maps [1], [2]. Furthermore, mobile platforms permit to track changes in exposure due to changes in human location and activities and provide new capabilities to evaluate health risk from air pollution [3], [4].

Several research projects are exploring the possibility of deploying low-cost sensor platforms to collect air quality data. H2020 CAPTOR (https://www.captor-project.eu/en/) project is one of them and it is based on the assumption that the combination of citizen science, collaborative networks and environmental grassroots social activism helps to raise awareness and find solutions to the air pollution problem, having a high potential impact on fields such as education, social innovation, science, environment, politics and industry. For that purpose three testbeds with around 170 sensor devices have been deployed in Spain, Austria and Italy with low-cost ozone (O_3) and nitrogen dioxide (NO_2) sensors mounted on wireless nodes. However, one key concern about these technologies is the uncertainty of their data. In fact, data quality in low cost based sensor networks is associated with several challenges [5] since data can be subject to many different types of faults. In a real sensor network deployment, Buonadonna et al. [6] observed that failures can occur in unexpected ways which provide inaccurate data.

Sensor calibration, [7], in low-cost based WSN is an inevitable requirement due to the natural process of device imperfection and noises in the massive data collected. Manual and automatic sensor calibration/re-calibration is essential, yet challenging for different reasons. One key reason is that often no direct means of sensor calibration was being provided by the sensor manufacturer. Second, even if sensors are calibrated before deployment, it is not possible to prevent sensor drift after deployment, especially when the lifetime of sensor systems can be as long as years. Thus, it is necessary to automatically calibrate sensors against drifts to correct sensor measurements after deployment to ensure the trustworthiness of long-term WSNs. Sensor calibration along this paper is considered herein when the data from array of sensors are fused to estimate calibration parameters of the low-cost sensor devices.

In this paper we calibrate more than 100 air pollution metal-oxide ozone sensors in a real network deployment. There are few papers in which i) commercial sensors are calibrated in a real deployment, and ii) a large amount of sensors are calibrated. Moreover, few is known on whether the sensors of the same manufacturer behave equally. In our work, we show that sensors of the same family behave quite different, showing a high variability in terms of Root Mean-Squared Error (RMSE). Knowing this variability, we mounted four

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metal-oxide ozone sensors at each node and a temperature and relative humidity sensors, adding redundancy with the ozone sensors and correcting the ozone concentration by taking into account other parameters by using an array of sensors. In this way, it is possible to reduce the amount of uncertainty in choosing the sensor that better reduces the RMSE. A second scenario is to fuse the data from all sensors in the same node. We compare three data fusion techniques: multivariate linear regression (MLR) fusion, average of data and median of data.

The outline of the paper is as follows. Section II enumerates the related work. Section III describes the testbeds and data sets used for the analysis. Section IV provides some preliminaries on single sensor calibration using multiple regression techniques for arrays of sensors. Section V presents data analytics for calibration using multivariate regression applied to sensor fusion for arrays of sensors. Finally, concluding remarks are made in Section VI.

II. Related work

There exists a broad range of calibration techniques developed to correct measurement errors in sensor networks which have been applied in different fields including air quality monitoring [8], [9], weather [10], localization [11], synchronization [12], target discovery [13], and many others. Most of the existing calibration approaches are built upon a number of assumptions such as the availability of high-quality reference measurements, prior knowledge on the true signal and/or the error model, redundant measurements, spatial and/or temporal correlation, mobility, and nodes interaction/cooperation. This helps in providing some basic information required for establishing the calibration process.

Calibration techniques can take a number of attributes [7] that define a calibration architecture. These attributes depend on whether the calibration is done in a given point or a given area (micro/macro or at device/system level), the knowledge on the physical phenomena (blind/non-blind/semi-blind calibration), the moment of calibration (pre-post-deployment/periodic/opportunistic), the position of the sensor with respect other already calibrated nodes (collocated/model-based/multi-hop), how the information is processed (off-line/on-line) and where (centralized/distributed), and finally the number of sensors (single/fusion of sensors) used simultaneously in calibration. Depending on the application and on the measured signal, the calibration architecture may have a combination of these attributes.

In air quality monitoring, non-blind calibration is generally employed in which gas and temperature sensors are calibrated leveraging on *ground-truth* data from high-quality instruments. Accordingly, the calibration parameters are adjusted using these known data inputs. There are organizations in many countries such as the European Environment Agency (EEA, http://www.eea.europa.eu/data-and-maps/data/airbase-the-european-air-quality-database-7) or United States Environmental Protection Agency (EPA, https://www.epa.gov/outdoor-air-quality-data) that openly publish data from high accurate reference stations deployed in these countries by public organizations to measure air pollution. These reference stations are not densely deployed due to their high costs, around 100K€(in dollars is around similar prices), but they can be used to calibrate low-cost sensors located behind them.

On the other hand, *sensor fusion* or *multi-sensor data fusion* is the technique that combines data from two or more sensors into a single one that provides a more accurate description than any of the individual sensors. Several approaches can be considered for sensor fusion. Tan et al. [13] propose a two-tier system-level calibration of a sensor network. In the first step, each sensor learns and transmits its local sensing model to a head node also called fusion-head. The received sensors' measurements are fused in the second tier where a common model is established and sensors are globally calibrated to optimize the system wide performance. Similarly, Fabeck and Mathar [14] propose a Bayes optimal fusion rule for a network of nodes that send measured data to a centralized node according to a binary hypothesis testing problem for detecting the presence of a target. Gao et al. [15] used multi-sensor fusion of four sensors attached to the waist, chest, thigh, and side of the body for activity recognition.

However, the most common approach for air pollution sensors is to reduce calibration errors by jointly considering the measurements of multiple sensors. This technique is called *array of sensors* and has as goal to reduce the uncertainty of calibration parameters in the data model. Arrays of different classes of gas sensors, [16], have proven quite useful to qualitatively identify gas species using pattern recognition approaches and quantitatively determine gas composition based on regression methods and for studying sensor devices from different manufacturers, [9], [17].

Our paper analyses the calibration of ozone sensors in a real Wireless Sensor Network deployment testbed. The approach taken is in the line of [17] that uses arrays of sensors to evaluate and compare the performance of gas sensor devices.

III. Testbed and Data set description

Gas sensors (e.g., CO_2, O_3, NO_2 gases) are sensors that follow multiple linear responses. Tropospheric ozone, (O_3), formation occurs when nitrogen oxides (NOx), carbon monoxide (CO) and volatile organic compounds (VOCs), react in the atmosphere in the presence of sunlight. In order to calibrate the O_3 sensors and depending on the type of sensor (metal-oxide or electro-chemical), it is needed to measure O_3, NO_2, temperature and relative humidity, [9], [17]. Experiments to measure O_3 have been performed in the H2020 CAPTOR project testbeds in Spain, Italy and Austria during the 2017 summer ozone campaign. The testbed consists of two types of nodes. The first one called *Captor* and built by UPC, Barcelona, Spain, following the DIY (Do It Yourself) philosophy, uses Arduino technology with a sensor shield board that attaches four SGX Sensortech MICS 2614 metal-oxide O_3 sensors in each Captor node, a temperature (Temp) sensor and a relative humidity (RH) sensor, Figure 1. Each Captor node is powered from an external power supply and it is connected to Internet

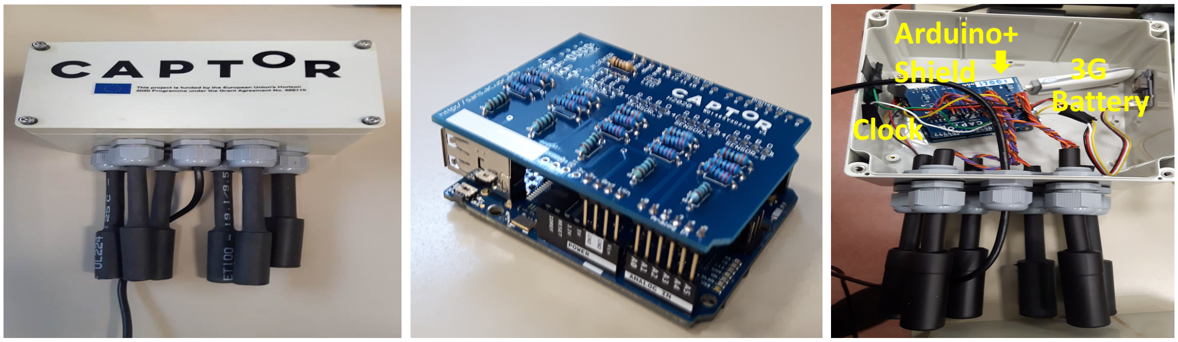

Fig. 1. Left) Captor node, Middle) Arduino Yun + sensoring shield, Right) Captor node box with its components.

using Wifi or 3G. The second type of node called *Raptor* and built by Limos-UCA, France, uses Raspberry technology with one αSense O3B4 electro-chemical O_3 sensor, one αSense NO2B4 electro-chemical NO_2 sensor, a temperature sensor and a relative humidity sensor. The Raptor outdoor node is powered by a 9V 4000mAh battery for a lifetime of 3 months, and connected using a IEEE802.15.4 (ZigBee) wireless access medium to a indoor Raptor local server, powered from an external power supply and connected to Internet using Wifi or 3G. Three testbeds have been deployed from June to September, 2017 in Spain, Austria and Italy, comprising 25 Captor nodes in Spain, 20 Raptors in Austria and 15 Raptors and 10 Captors in Italy. There are in total 150 metal-oxide O_3 sensors and 35 electro-chemical O_3 and NO_2 sensors deployed. In this paper, we will focus the research in the captor nodes calibrated in the Spanish Testbed.

For calibration, nodes have been first locally tested in reference stations nearby the places were the nodes were built, and then in reference stations nearby the final deployment location of the nodes. The calibration is considered to be of type off-line, non-blind, centralized calibration, [7]. We will select a Data Set considering Captor nodes located at 3 reference stations in Spain: i) 6 Captor nodes calibrated at Palau Reial reference station in Barcelona town, Spain (41°23'14"N, 2°6'56"E), operated by CSIC (Spanish National Research Council) and the Regional Government of Catalonia (Spain), ii) 7 Captor nodes calibrated at Manlleu reference station (42°0'6.966"N, 2°17'13.7868"E) and, iii) 12 Captor nodes calibrated at Tona reference station (41°50'49.7796"N, 2°13'14.7864'E), these operated by the Regional Government of Catalonia (Spain).

The nodes have been placed from 3 to 4 weeks in the reference stations and samples have been taken every hour. Internally, every sample is the average of a set of multiple consecutive samples taken during an interval of 5 minutes and with outliers eliminated. When the final sample is obtained, it is then sent via a wireless communication to a Database in a repository where the sensor can be off-line calibrated. Finally, the nodes are deployed in volunteer houses in the country-side. The estimated coefficients are uploaded via the wireless communication and from that moment, all O_3 concentration values measured in the volunteer houses are predicted in the node and sent on real-time to a server that can be consulted via a smart-phone app or using a browser in a tablet or PC.

IV. Data analytics for calibrating sensors using multiple array of sensors

Let us consider an array of M sensors, a Multiple Linear Regression (MLR) model accommodates M predictors, one for each sensor, taking the form of [18]:

$$y_k \sim f(\beta, x_k) = \beta_0 + \sum_{j=1}^{M} \beta_j x_{kj} + \epsilon_k \qquad k = 1, ..., K \quad (1)$$

where ϵ_k is a random error term, Gaussian distributed with zero mean and variance σ^2. The model assumes that y is a vector of K samples with the ground-truth or calibrated values, and x_j (j=1,...,M) are vectors of size K with the data measured by each of the M sensors with the uncalibrated values. The *offset* arises when the measured value Y differs from its true value X by a constant amount β_0 and can be determined by measuring the sensed value when the ground-truth value is zero. The *gain* refers to the rate or the amount of change of the measured value with respect to the change in the underlying ground-truth value, and it is represented by coefficients β_j with j=1,...,M. For commodity, we define a vector of ones with size K and integrate the coefficient β_0 in the summation:

$$y_k \sim f(\beta, x_k) = \sum_{j=0}^{M} \beta_j x_{kj} + \epsilon_k \qquad k = 1, ..., K \quad (2)$$

and express the former equation in vectorial form as $\mathbf{y} = \mathbf{X}\beta + \epsilon$, where we denote the columns of the **design matrix** $\mathbf{X} \in \mathrm{R}^{K \times (M+1)}$ by $\mathbf{x}_0, ..., \mathbf{x}_M$, where $\mathbf{x}_0 \in \mathrm{R}^K$ is a vector of 1's that capture the offset, $\mathbf{x}_j \in \mathrm{R}^K$ with (j=1,..., M) and vector $\mathbf{y} \in \mathrm{R}^K$ is the ground-truth data. Then, the calibration coefficients can be obtained by solving the least-squares minimization problem:

$$\hat{\beta}_{LS} = \text{arg min}_{\beta} ||X\beta - y||_2^2 \quad (3)$$

The calibration parameters β^*'s are the solution of the minimization problem. The error is non-negative except whenever the function f(β,x_k) pass exactly through each target point y_k in which case the error will be zero. Calling $\hat{y}_k$=f(β^*,x$_k$),

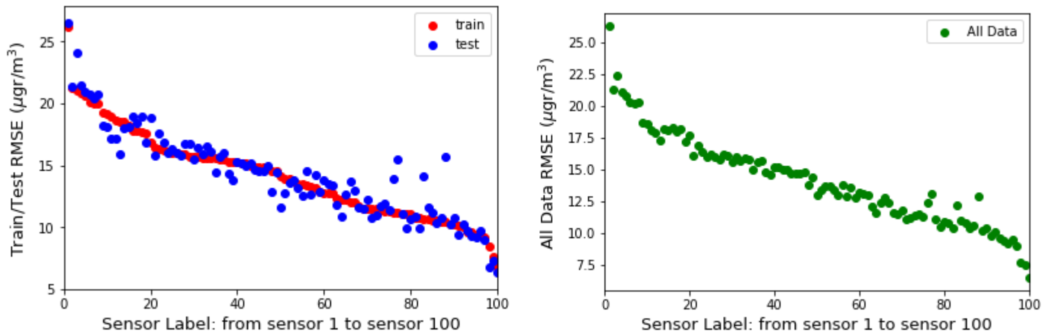

Fig. 2. Calibration of 100 O_3 sensors: Left) Train and Test RMSE, Right) RMSE for the whole data set.

The *Root Mean-Squared error (RMSE)* [18] allows to compare different sizes of data sets in the same scale than the target value y_k:

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}(\hat{y}_k - y_k)^2} \tag{4}$$

Finally, the R^2 *(Coefficient of Determination)* measures the proportion of variability in Y that can be explained using X and it is bounded between 0 and 1. When R^2 is close to 1 indicates that a large proportion of the variability in the response has been explained by the regression.

It is well known, that the calibration of O_3 depends of O_3, temperature and relative humidity, [17], [19]. Thus, M=3 and $y \sim \beta_0 + \beta_1 O_3 + \beta_2 Temp + \beta_3 RH$. We have taken the 25 nodes deployed in the 3 reference stations in Spain, and we have calibrated the 100 sensors. For each sensor, the data set has been split in two parts: the *training set* formed by 65% of the data set has been used for estimating the coefficients, while the *test set* formed by the other 35% has been used for validating or predicting the data.

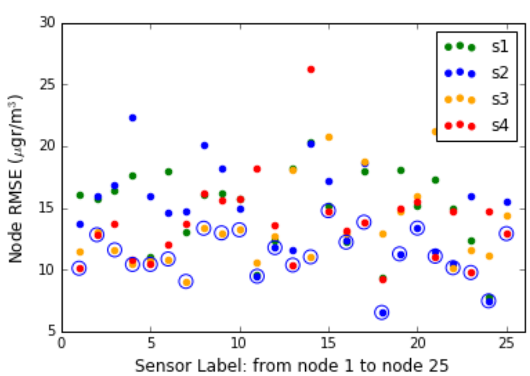

Fig. 3. Sensor RMSE per node, the largest circle indicates the sensor with lowest RMSE among the 4 sensors at each node.

Figure 2 shows the RMSE for each sensor device. Red dots in Figure 2.Left) represent the training RMSE (in μgr/m^3) for each sensor device. Sensors are ordered from highest training RMSE to lowest training RMSE. The blue dots represent the test RMSE. The test RMSE is obtained over the test data set using the estimated coefficients calculated over the training set. Figure 2.Right) shows the overall RMSE over the whole data set. We may observe several issues:

- There is a large variability between the whole set of sensors. The average amount of O_3 in the three areas considered is of 60 μgr/m^3 in Palau Reial reference station, 88 μgr/m^3 in Tona reference station and 65 μgr/m^3 in Manlleu reference station, with peaks in summer that can range between 180-200 μgr/m^3. The largest RMSE is of around 26 μgr/m^3 while the lowest is around 7-8 μgr/m^3 depending on the sensor device, all from the same manufacturer. That means that installing one or other sensor device from the same family impacts the quality of the data obtained irrespectively of the calibration process.
- The difference between the training and test RMSE remains almost constant, few units, for all sensors. That means that when an improvement is obtained in the training set, the test RMSE can be at most a couple of units below or above the training RMSE.

Each captor node mounts 4 O_3 sensor devices, chosen randomly from the set of sensors bought to the manufacturer. One of the objectives was to add redundancy due to the high RMSE variability. Figure 3 shows the RMSE classifying them at each node, it is to say, each captor node is labeled from 1 to 25 and in the y-coordinates, the RMSE for the whole data set is shown for each of the 4 sensors, labeled as s1, s2, s3 and s4. We can observe that:

- For each node, the RMSE variability is high. However, having 4 sensors installed, allows us to choose as representative of that node the sensor with lowest RMSE, marked with a largest circle in the figure. Moreover, in case of failure, there is a second choice and so on, although giving worst data predicted quality. As an example, captor node labeled 14 has sensors s4 and s2 with RMSEs larger than 20 μgr/m^3 while sensors s1 and s3 are very close to each other with RMSEs between 11 and 12 μgr/m^3.

Figure 4.Left) and 4.Right) show the calibrated data for two sensors in the same node called captor C-17012 located in Tona Reference Station. The majority of tropospheric ozone formation occurs when nitrogen oxides (NOx), and volatile

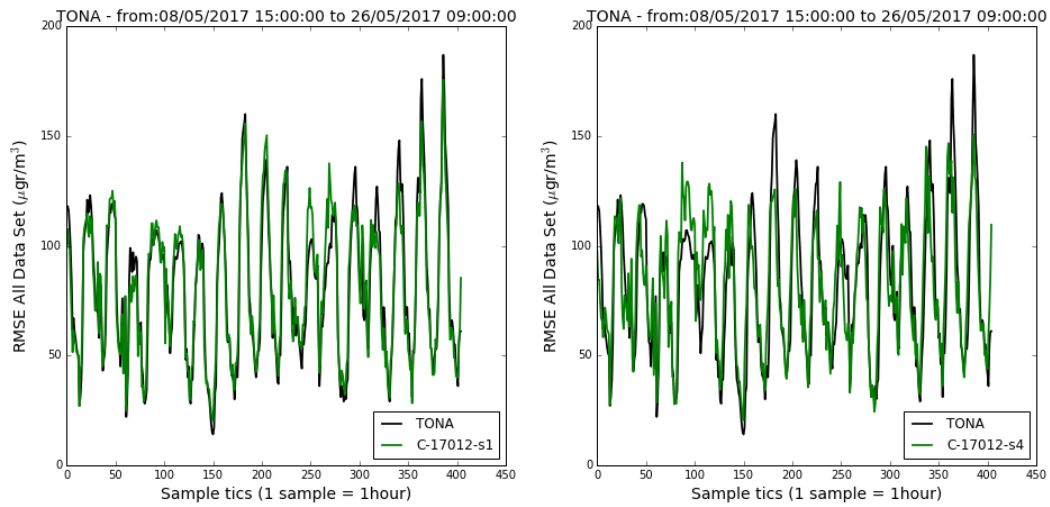

Fig. 4. Calibrated Ozone for captor node number 17012, Left) sensor s1, with RMSE 9.60 μgr/m^3, Right) sensor s4, with RMSE 18.17 μgr/m^3

organic compounds (VOCs) such as carbon monoxide (CO), react in the atmosphere in the presence of solar radiation. It is well known that ozone increases during the day due to solar radiation and NO_2, that produces O_3 and NO_x while reduces at night when combining O_3 with NO_x in the absence of solar radiation. This causes that the calibrated values cycle every 24 hours (samples) from high values at day to low values at night, Figure 4.Left,Right). The plots show the best sensor, s1 in this case, and the worst sensor, s4 in the case of the four O_3 sensors mounted in the same captor node. There are 450 samples, each sample representing a tic of 1 hour, giving a total of 450 hours of measures. We can observe that:

- The calibration using an array of sensors and multivariate regression allows to calibrate O_3 metal-oxide sensor devices. However, the results are quite dependent on the sensor device technology. Some sensors are not able to reach the whole dynamic range of the true concentrations of ozone as can be observed in Figure 4.Right). In this figure, it is observed, and this was observed in other sensor devices of the same family, that the sensor device s4 does not reach large concentrations of ozone, e.g., larger than 150 μgr/m^3 while sensor s1 is able to reach such large concentrations.

V. Data analytics for calibrating sensors using data fusion

Given that each captor node has mounted 4 metal-oxide sensor devices, we can question whether a fusion of the four sensors can improve the estimation of the true concentration of the physical phenomena. Defining as M=4 the number of Ozone sensors, sensor M+1 as the temperature sensor and sensor M+2 as the relative humidity sensor, a multiple linear regression (MLR) fusion can be expressed in vector form as:

$$y \sim f(\beta, x) = \beta_0 + \sum_{j=1}^{M} \beta_j O_{3_{sj}} + \beta_{(M+1)} Temp + \beta_{(M+2)} HR + \epsilon \tag{5}$$

The idea is that instead of choosing the best sensor as representative of the captor node, there is a *virtual value* that represents the node and gets contributions of each of the 4 O_3 sensors that measure the physical phenomena. As in the previous case, sensors for temperature and relative humidity are added in the array of mounted sensors since the physical phenomena depends on temperature and relative humidity. Finally, we include two other fusion mechanisms typically used in sensor fusion literature: i) the virtual calibrated value for each sample is the average of the four sensor calibrated values, ii) the virtual calibrated value for each sample is the median of the four sensor calibrated values.

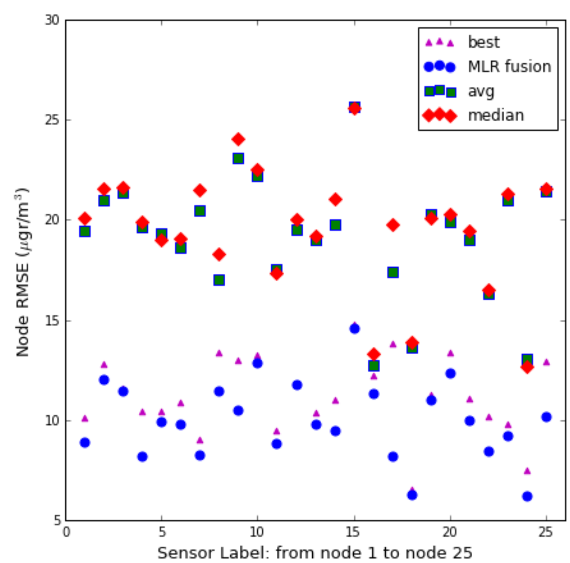

Fig. 5. Sensor RMSE per node, the magenta indicates the RMSE for the best sensor without fusion, the black indicates the RMSE for the fusion of 4 sensors for each captor node.

Figure 4.Left,Right) shows RMSEs for sensor s1 and s4 of 9.60 μgr/m^3 and 18.17 μgr/m^3 (best and worst sensors of

Captor node 17012). With the MLR fusion of sensors, the RMSE goes down to 8.85 μgr/m^3, showing and improvement with respect the best sensor. In order to observe if this trend is common to all the nodes, Figure 5 shows the RMSE for the best sensor for each captor node and the RMSE for the fusion of sensors for each of the 25 captor nodes. As it can be observed in all of the captor nodes there is an improvement in the RMSE using the MLR fusion of sensors in comparison to the best of the 4 O_3 sensors. There are some cases in which this improvement is almost negligible, on the other hand, in other cases the difference reached 5-6 μgr/m^3 units. MLR fusion is much better than using the average to the median. The reason is that the worst sensors penalize the average and median. On the other hand, the MLR fusion regression obtains the best calibration coefficients for all the sensors. In any case, we can conclude that having an array of sensors that measure the same physical phenomena has several advantages. In case of failure of the sensor device, there are back-up sensors able to still measure the physical phenomena. Moreover, fusing the O_3 we were able to decrease the RMSE even further below the best sensor of the same family.

VI. Conclusions and Future Work

In this study, we have investigated the performance of commercial low-cost Ozone sensors mounted in a WSN for air quality monitoring through sensor calibration. First, the wireless sensor testbed has been described, including the hardware used for having an array of Ozone, temperature and relative humidity sensors. A study of the calibration of Ozone concentrations using these array of sensors shows that using multivariate estimation techniques allows to calibrate the Ozone sensor devices. However, these devices show a high variability, meaning that the RMSE is quite different for the same family of manufacturer devices. Having also an array of Ozone sensors allows to increase the reliability by choosing the sensor in the set of Ozone sensors with best RMSE. On the other hand, using the whole set of Ozone, temperature and relative humidity sensors and producing a fusion of data it is possible to further reduce the RMSE and then improve the predicted Ozone concentrations. We have not seen other papers that use more than one sensor in the same node to measure a physical phenomena, adding redundancy to the sensing subsystem. As future work, we believe that instead of using multivariate frequentist regression, there are other techniques to improve the RMSE, as can be hierarchical Bayes regression. Moreover, the scatter-plots show certain non-linearities, which make us think that probably non-linear estimating models can also improve the calibration.

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References

[1] D. Hasenfratz, O. Saukh, C. Walser, C. Hueglin, M. Fierz, T. Arn, J. Beutel, and L. Thiele, "Deriving high-resolution urban air pollution maps using mobile sensor nodes," *Pervasive and Mobile Computing*, vol. 16, pp. 268 – 285, 2015.

[2] P. Schneider, N. Castell, I. Vallejo, M. V. W. Lahoz, and A. Bartonova, "Data fusion of crowdsourced observations and model data for high-resolution mapping of urban air quality," in *10th International Conference on Air Quality Science and Application*, March 2016, p. 76.

[3] J. Van den Bossche, J. Theunis, B. Elen, J. Peters, D. Botteldooren, and B. De Baets, "Opportunistic mobile air pollution monitoring: A case study with city wardens in antwerp," *Atmospheric Environment*, vol. 141, pp. 408–421, 2016.

[4] A. De Nazelle, E. Seto, D. Donaire-Gonzalez, M. Mendez, J. Matamala, M. J. Nieuwenhuijsen, and M. Jerrett, "Improving estimates of air pollution exposure through ubiquitous sensing technologies," *Environmental Pollution*, vol. 176, pp. 92–99, 2013.

[5] A. Kotsev, S. Schade, M. Craglia, M. Gerboles, L. Spinelle, and M. Signorini, "Next generation air quality platform: Openness and interoperability for the internet of things," *Sensors*, vol. 16, no. 3, 2016.

[6] P. Buonadonna, D. Gay, J. M. Hellerstein, W. Hong, and S. Madden, "Task: sensor network in a box," in *Wireless Sensor Networks, Second European Workshop, EWSN, Istanbul, Turkey, January 31 - February 2, 2005, Proceedings*, 2005, pp. 133–144.

[7] J. Barcelo-Ordinas, M. Doudou, J. Garcia-Vidal, and N. Badache, "Calibration techniques and methods for uncontrolled environments in sensors networks: A reference survey," *submitted to ACM Transactions on Sensor Networks*, 2017.

[8] C. Xiang, P. Yang, C. Tian, H. Cai, and Y. Liu, "Calibrate without calibrating: An iterative approach in participatory sensing network," *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, no. 2, pp. 351–361, Feb 2015.

[9] L. Spinelle, M. Gerboles, M. G. Villani, M. Aleixandre, and F. Bonavitacola, "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*, vol. 238, pp. 706–715, 2017.

[10] Y. Yu and H. Li, "Virtual in-situ calibration method in building systems," *Automation in Construction*, vol. 59, pp. 59 – 67, 2015.

[11] S. Bolognani, S. Del Favero, L. Schenato, and D. Varagnolo, "Consensus-based distributed sensor calibration and least-square parameter identification in wsns," *International Journal of Robust and Nonlinear Control*, vol. 20, no. 2, pp. 176–193, 2010.

[12] M. S. Stankovic, S. S. Stankovic, and K. H. Johansson, "Distributed blind calibration in lossy sensor networks via output synchronization," *IEEE Transactions on Automatic Control*, vol. 60, no. 12, pp. 3257–3262, Dec 2015.

[13] R. Tan, G. Xing, Z. Yuan, X. Liu, and J. Yao, "System-level calibration for data fusion in wireless sensor networks," *ACM Trans. Sen. Netw.*, vol. 9, no. 3, pp. 28:1–28:27, Jun. 2013.

[14] G. Fabeck and R. Mathar, "In-situ calibration of sensor networks for distributed detection applications," in *International Conference on Intelligent Sensors, Sensor Networks and Information*, Dec 2007, pp. 161–166.

[15] L. Gao, A. K. Bourke, and J. Nelson, "A system for activity recognition using multi-sensor fusion," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug 2011, pp. 7869–7872.

[16] Y. Liu, K. Zhou, and Y. Lei, "Using bayesian inference framework towards identifying gas species and concentration from high temperature resistive sensor array data," *Journal of Sensors*, vol. 2015, 2015.

[17] L. Spinelle, M. Gerboles, M. G. Villani, M. Aleixandre, and F. Bonavitacola, "Field calibration of a cluster of low-cost available sensors for air quality monitoring. part a: Ozone and nitrogen dioxide," *Sensors and Actuators B: Chemical*, vol. 215, pp. 249–257, 2015.

[18] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An introduction to statistical learning*. Springer, 2013, vol. 6.

[19] B. Maag, O. Saukh, D. Hasenfratz, and L. Thiele, "Pre-deployment testing, augmentation and calibration of cross-sensitive sensors," in *Proceedings of the 2016 International Conference on Embedded Wireless Systems and Networks*, ser. EWSN '16. USA: Junction Publishing, 2016, pp. 169–180.