Proceedings

Reliable Long-Term Data from Low-Cost Gas Sensor Networks in the Environment †

Georgia Miskell [1], Jennifer Salmond [2], Stuart Grange [1], Lena Weissert [1], Geoff Henshaw [3] and David Williams [1,*]

[1] School of Chemical Sciences, University of Auckland, Auckland, New Zealand; georgia.miskell@auckland.ac.nz (G.M.), s.k.grange@gmail.com (S.G.); lwei999@aucklanduni.ac.nz (L.W.)
[2] School of Environment, University of Auckland, Auckland, New Zealand; j.salmond@auckland.ac.nz
[3] Aeroqual Ltd., Auckland, New Zealand; geoff.henshaw@aeroqual.com
[*] Correspondence: david.williams@auckland.ac.nz
† Presented at the Eurosensors 2017 Conference, Paris, France, 3–6 September 2017.

Abstract: This poster examines long-term performance of low-cost instruments in environmental networks using a semiconducting oxide sensor measuring ground-level ozone (O_3). Sensors were placed outside in networks and automated methodologies based on knowledge of sensor and environment characteristics were successfully applied to confirm sensor stability. These networks demonstrated how environmental data could be collected and confirmed using networks of low-cost sensors, which supplemented observations from the existing regulatory network. This work is a critical step in the development of networks of low-cost environmental sensors when considering the delivery of reliable data.

Keywords: low-cost; environment; long-term stability

1. Introduction

Low-cost sensors are increasingly being used in environmental research [1]. They offer flexibility and opportunity to explore hypotheses previously too difficult to test [2]. The numerous benefits of this technological development has led to a growing body of work; however, the delivery of good quality data is key, and in the literature trade-offs are often mentioned [3]. A critical issue is confirming the integrity and calibration of the sensor over time. Common issues in sensors can be effects of ambient conditions (e.g., sublimation of sensor material from high humidity [4], increasing baseline measurements [5], drifting calibration, and site impacts (e.g., dirt in inlets or power variations). Identifying changes in baseline or calibration so that action can be taken would improve management of such networks. This is a more than simply detecting change, as the need is to distinguish changes in the sensor to changes in the environment. Further, sensors often demonstrate good lab calibration performance in, which is then lost in the field [6]. Understanding why this happens, and the development of mitigation or correction strategies to offset this, is important in developing confidence in sensor data. Our work is directed at the development of methods for confirming long-term stability and detecting change of low-cost sensors in the field, and illustrates the potential within an ozone network around Auckland, New Zealand.

2. Materials and Methods

2.1. Drift Characteristics

Low-cost commercial devices based on a semiconducting oxide sensor measuring ozone (O_3) were redesigned for long-term environmental measurement by reconfiguring the device and using

the cell-phone network. The sensor is a non-linear device, with O_3 derived from two measured resistances: a gas resistance, R_g, and a baseline resistance, R_b, obtained by dropping air-flow rate over the sensor. There are a number of empirical functions that can be used to calibrate the sensor. In [5], we illustrated a function derived from a theoretical model of the sensor response, (P):

$$P = (R_g - R_b)/(a_b R_b R_g - b_g(R_g - R_b)), \tag{1}$$

where a_x and b_x are device parameter functions set according to the instrument heating time step.

However, a different function, derived from an empirical power-law model for the response, is also reasonable to deliver a corrected sensor reading:

$$P = a_b(R_g/R_b)^{ag} \tag{2}$$

The parameters for these two functions are dependent on the microstructure of the sensor [7,8] and on the operation of the device, particularly air-flow rate. If the device parameters remain stable then (1) and (2) should give, within some acceptable error, the same result, P, for any pair of R_g and R_b. However, if the sensor drifts, that is if the parameter values were to change, then it would be unlikely these two calculations would give the same result. Thus, if it were possible to compare both results over time with the original calibration parameters, then sensor drift would be signaled by a change. A second function, however, may not be available for comparison, which would normally be the case, as in the present work. However, a comparison could be made by a suitable plot of P against some combination of R_b and R_g, which we denote here as $h(R_b, R_g)$ where h depends only on gas concentration and device parameters and not the measured numbers:

$$h(R_b, R_g) = H(P, b_b, b_g, \dots) \tag{3}$$

In operation, as atmospheric O_3 changes, plotting (3) against P, would trace a curve which we term the operating line for the device. If the reported O_3 concentration is plotted against $(R_g - R_b)$, in effect comparing (2) to (3) where (3) = $R_g - R_b$, then the result varies along a curve as ambient O_3 naturally varies. If the sensor is stable then the resulting curve should not vary from the operating line, but if the sensor parameters drift then the operating line will shift over time.

2.2. Empirical Detection Methods

Empirical methods to identify change in concentration over time have been discussed in [9]. Briefly, we used two tests (Kolmogorov-Smirnov (KS) and Mean Variance (MV) that created both a variance ratio and effect size metric) to identify any shift in the indicated concentration probability distribution, relative to the network. Due to natural local-scale events that can cause periodic error signals, a persistence threshold was applied that required a steady flow of alarms over time (similar to control system processes). These methods used only the sensor concentration in order to make them applicable to any sensor and to allow for automation of tests. These tests allowed for better quality data capture, and minimized length of response time. It also allowed for an objective, statement on data quality that supported the network manager in making decisions.

3. Results

Figure 1 illustrates a sensor that had an increasing and unstable R_b over time. The sensor was returned to the lab and compared against a Model 49i Thermo O_3 analyzer where it was observed to record higher values and suppressed diurnal pattern. However, O_3 response remained high ($R^2 = 0.92$) and so, following post-calibration, sensor data was salvageable.

Equation (3) against P successfully detected drifting sensors (Figure 2). The running statistical tests were also successful in identifying sensor drift, with many divergences detected within one-week (Figure 3). The MV test was found to give more robust results due to error thresholds being set by practical limits. The KS test is defined by a probability distribution that relies on concentration range and is prone to statistical significance (which may not be of practical significance). These tests illustrated their use in automated management of network, as daily reporting allowed the network
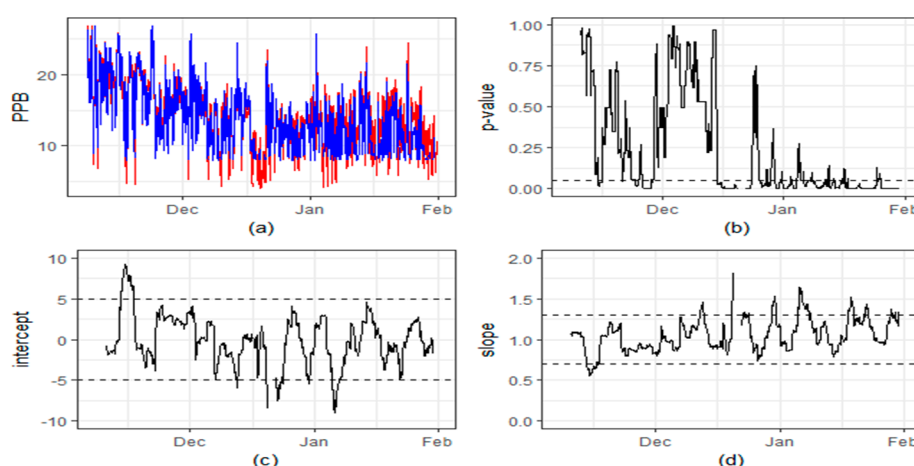
manager to have an objective opinion on the state of each sensor, and optimise time spent on maintenance.
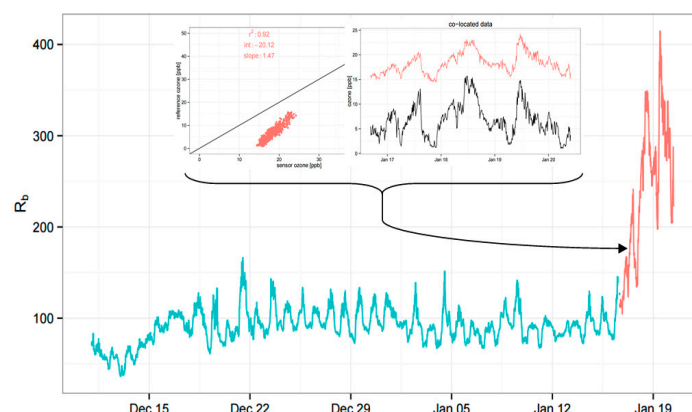
Figure 1. Sensor baseline (R_b) where it increased (pink). Inset: co-location correlation and time-series to analyzer (black) during the unstable baseline period.

(**a**)   (**b**)
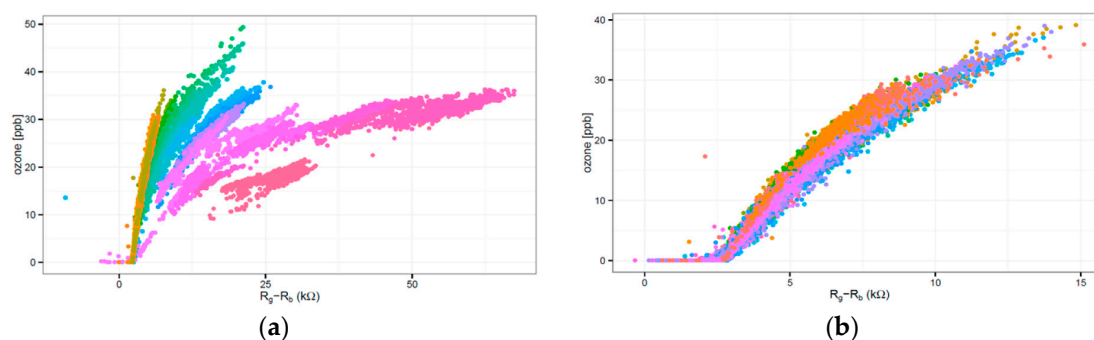
Figure 2. Sensor gas (R_g)—sensor baseline (R_b) over time (**a**) Unstable baseline; (**b**) Stable baseline.

(**a**)   (**b**)

(**c**)   (**d**)

Figure 3. (**a**) Co-located sensor measurements; (**b**) KS-test *p*-value output; (**c**) MV-test intercept output; (**d**) MV-test slope output.

A network of sensors (n = 12) were used to reveal O_3 patterns not identified in the regulatory network (n = 3) around Auckland, New Zealand. Examination of instrument siting, where surroundings may affect concentrations, showed good agreement to analyzers within 20 km [10]. No bias was identified between those sensors placed on regulatory stations and those sensors placed upon walls or balconies, giving confidence that both instrument and siting did not affect the reported data. Overall, O_3 was low across Auckland, which is believed due to low background concentrations,

low long-range transport, and NOx titration. Low concentrations were found for those locations in residential settings, especially during commuting periods and at night [11].

4. Discussion

Low-cost semiconductor sensors were successfully used in a long-term air-quality network, with characterization of calibration drift using data-driven algorithms. This sensor network demonstrated that when operated using automated data quality checks, these sensors could be used in environmental science to provide unique supplementary information to existing regulatory networks.

Conflicts of Interest: D.W., G.S. shareholders in Aeroqual Ltd. Funding sponsors had no role in design of the study; in collection, or analysis of data; in writing the manuscript, or in decision to publish results.

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