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BEYOND THE ERROR: UNVEILING UNCERTAINTIES IN PRESSURE SENSOR MEASUREMENTS

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ABSTRACT

In every sensor lies inherent uncertainty. It is crucial to distinguish between error, accuracy, and uncertainty. Error reflects the discrepancy between an exact and measured value, a difference often elusive due to the inaccessibility of the 'exact' value. Uncertainty denotes the range of plausible values attributed to a measurement.
For accuracy, understanding the nature of uncertainty and defining the confidence interval is essential. Statistically, broader confidence intervals imply greater uncertainty. For instance, for a normal distribution, 68.3%, 95.4%, and 99.7% confidence intervals are typically represented by σ1, σ2, and σ3, respectively. Many datasheets cite accuracy in terms of average values, with a variation roughly equivalent to σ1.
Calibrating sensors involves many components, including reference pressure sensors and temperature sensors, power supplies, interface cards, and acquisition equipment. Each has its inherent uncertainties which cumulatively influence the tested sensor. It is not known but most of the uncertainty (50% to 80%) is attributed to the test bench used to calibrate/test the sensor. That is what we will show in this paper.

There are several methodologies to evaluate uncertainties.
Primarily, two main methods can be distinguished:

- **Type A**: This approach focuses on repetitive measurements of a single component. It is thorough and often yields more precise uncertainties specific to that element. However, its detailed nature can be time-consuming.
- **Type B**: This method leans on datasheets provided by manufacturers. It is faster, but can lead to broader uncertainties, especially if based on generalizations drawn from large component batches. When manufacturer data is lacking or insufficient, resorting to Type A becomes necessary.

Regarding pressure sensors, their operation is defined by a linear equation linking the applied pressure with the output and supply voltage. Using a model to represent this relationship inherently introduces another layer of uncertainty. It is worth noting that no model can perfectly match every data point, hence certain deviations will always exist. The objective is to determine the sensor's transfer function using the least squares method, which provides a clear understanding of its performance under varying conditions.

Keywords: pressure sensors, error, uncertainty, accuracy

NOMENCLATURE

MEMS Micro Electro-Mechanical Systems. In this paper it means piezoresistive MEMS. One of the technologies used for measuring pressure.

P	Pressure
S+ S-	Voltage at the output of the MEMS
T	Temperature
u_c	Uncertainty (of measurement)
V+ V-	Voltage applied on the pressure MEMS
LDO	Low Dropout Regulator
BFSL	Best Fitted Straight Line

1. Introduction

Sensorade, a Belgian company based near the famous Spa Francorchamps circuit, has developed a miniatured pressure sensor for absolute and relative pressure measurements, to be operated even in harsh environment (Figure 1 - Sensorade miniaturized pressure sensor). One of them is the smallest flow pressure sensor on the market, with a resonance frequency of 2.675 MHz, and is also able to measure flow temperature. Pressure sensors with a diameter of 10mm are commonly regarded as "small." However, the scale further reduces with sensors measuring a mere 1.2mm in diameter.

Figure 1 - Sensorade miniaturized pressure sensor

In various applications for different customers, miniaturized pressure sensors have proven instrumental in optimizing performance and precision. In the realm of automobile sports, real-time data from MEMS pressure sensors is utilized to fine-tune engine fluid dynamics, optimizing power output. Wind tunnels, crucial for aerodynamic research, benefit from these sensors, allowing for meticulous design and refinement for enhanced efficiency and reduced drag. In medical applications, particularly those demanding precise monitoring under minimal temperature differentials, Sensorade's pressure sensors play a vital role in controlling fluid flows in medical devices. This application extends to air conditioning systems, where these sensors facilitate finer control of refrigerant pressures, contributing to improved energy efficiency. Additionally, their esteemed client, Vestas, leveraged sensors for an innovative endeavor (ref. 1). They aimed to develop even longer wind turbines, potentially causing the tip speed to exceed 80 m/s and approach transonic speeds. In rigorous tests utilizing their sensors, Vestas explored the feasibility of achieving turbines with heightened efficiency at these elevated speeds. This initiative exemplifies the versatility of our sensors, applied not only in conventional contexts but also in cutting-edge projects that push the boundaries of technological innovation. Even in the context of test benches for turbomachinery and other applications, MEMS pressure sensors provide high-resolution measurements, enabling precise calibration and validation of designs. The versatility of these pressure sensors, applied across a spectrum of industries, underscores their role in advancing efficiency and precision. Before being operational, pressure sensors need to undergo calibration. Such calibration can be done with various methods (see ref. *2* for a framework proposition close to our test bench).

With such precision needed, it is essential to determine the uncertainty of the sensor measurements. Determining this uncertainty can be complex especially because most of the uncertainty (50% to 80% - see section 3.5 on **Test bench uncertainty contribution**) is attributed to the test bench used to calibrate the sensor, as already mentioned. This paper will analyze into details the uncertainty present in the measurements when using such a tiny pressure sensor and the main factor influencing the accuracy of such device. Of course, we will consider our own test bench to go into the details.

In order to compute the uncertainty present in our measurements, we followed the procedure advised by the following guide: "*Evaluation of measurement data —**G**uide to the expression of **u**ncertainty in **m**easurement."* (or **GUM**). The GUM is a document (ref. *3*) delivered by the BIPM (*Bureau International des Poids et Mesures)***.**

It is also important to evaluate the uncertainty attributed to linear regression methods, those are well known and discussed in papers such as ref. *4*.

2. Materials and methods

Uncertainty is present on all types of sensors. To quantify the uncertainties of the sensors, it is essential to consider the different factors of each uncertainty. First of all, it is important to distinguish uncertainty and error. An error, also misnamed accuracy, is the difference between the exact value and the measured value, but in all cases, the exact value is not known. The uncertainty, however, represents the spread of values that can reasonably be attributed to the measurement.

Sensor accuracy refers to a sensor's ability to produce results that are close to the true or expected value. It is often mistaken for other terms like correctness or repeatability, but in reality, it encompasses how closely individual measurements align with a reference value. Accuracy is a comprehensive concept that considers both trueness (absence of bias) and precision (variability of measurements).

When accuracy is required, we have to compare apples to apples. This means that we have to understand what we are talking about regarding uncertainty, and we have to define the confidence interval. A confidence interval is the range of values where our true value is expected to lie. From a statistical point of view, "The larger the confidence ranges the greater the uncertainty" is what we consider a "Normal" or Gaussian law.

In general, we consider 3 confidence interval sizes, as shown on Figure 2.

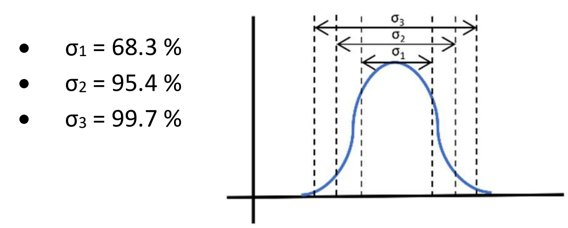

Figure 2 - Confidence intervals and standard deviation

The quantity σ represents the standard deviation of the measurements. It is important to understand that a lot of datasheets give accuracy values by mentioning the average value with a variation range equal to σ_1.

In this tutorial we summarize the different uncertainties that are encountered when calibrating pressure sensors. The following diagram shows the different elements that are necessary for a calibration. All calibrations require a reference pressure sensor that allows us to calibrate our sensors against it. A temperature sensor is particularly useful when we make calibrations at a specific temperature. Then, the power supply and the output

signal of the elements are managed by an interface card whose components can have an impact on the measurement of the sensors. Furthermore, it is necessary to add to this calibration an acquisition equipment that allows to receive the data from all the sensors, as well as a power source that supplies them.
Each of these elements have uncertainties that have an impact on the tested pressure sensor, it is the misnamed error or accuracy.

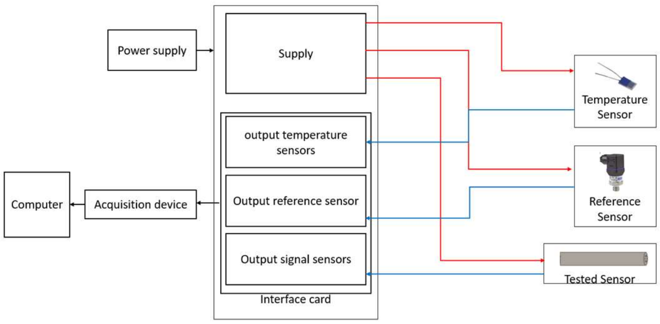

Figure 3 - Pressure sensor complete measurement chain

Power supply: **EL302R**, AIM & THURLBY THANDAR INSTRUMENTS
Reference sensor: **Keller PA(A)3310**, Keller
Temperature sensor: **PTF Family class B**, TE Connectivity
Acquisition device: **NI USB-6218**, National instruments
Interface card: Sensorade's custom board

The goal of this paper is to describe the methodology used to test and measure the pressure sensors. The main objective is to quantify the precision of those sensors or the uncertainty of the obtained measurement.
In the calibration setup, there is an acquisition board that is used to connect all the main components together. The board can link five absolute pressure sensors and a data acquisition device. This document will provide the capabilities (specifications, precision, etc.) of this board. A block diagram presents on Figure 4 the different elements of this acquisition board.

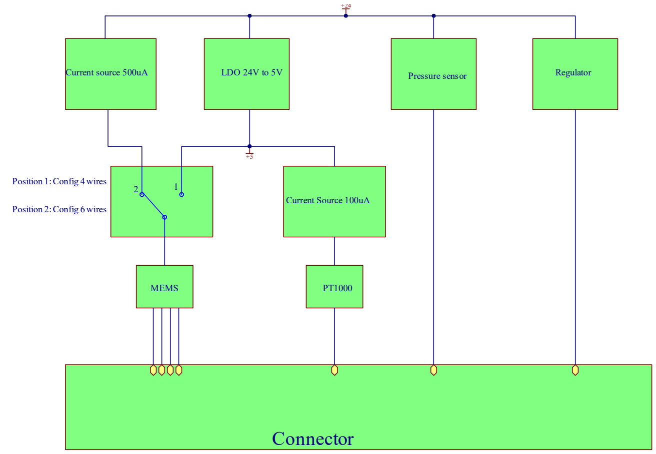

Figure 4- Block diagram of data acquisition strategy

From this block diagram, it is important to note that the MEMS can be powered either using a 0.5 mA current source or a 5V voltage source provided by an LDO.
Therefore, in this paper, when necessary, the source used to power the MEMS will be referred as "Voltage Source" or "Current Source". The current MEMS can be used to measure in the range 0-200 bar in a 0-200°C temperature range. Depending on the maximum pressure required, we will have to change the reference sensor. Until today, we have used 3 reference sensors.

2.1. Uncertainty computation

To get the most from this paper, it is highly recommended to be comfortable with the notions explained in the GUM. The goal will be to provide an uncertainty associated to our measurements.
In this paper, as suggested in the GUM, we will try, as much as possible, to avoid the term **error** and rather use the term **uncertainty**. The difference is well explained in the GUM (in the "*Annex B*"). Indeed, the error is the difference between the measurement and the true value. However, the true value cannot be determined, so using the term error is not ideal. While the uncertainty is like a parameter that *"characterizes the dispersion of the values that could reasonably be attributed to the measurand"*. However, in the datasheets, the term uncertainty is rarely used. Instead, precision or tolerance are often used. So, in this paper, all these terms will be translated in terms of uncertainty.
This uncertainty is always defined for a given confidence interval. That is why, here, all measurements are given for 3 main confidence intervals:

1. a 68,3% confidence interval or $\mathbf{1\sigma}$
2. a 95,4% confidence interval or $\mathbf{2\sigma}$
3. a 99,7% confidence interval or $\mathbf{3\sigma}$.

A confidence interval is a range of values that we are relatively sure the true value lies in. So, after taking a set of measurements for the same value of the measurand, the uncertainty on the

results will depend on the confidence interval. The higher the confidence interval, the higher the uncertainty.
To get the uncertainties, we follow the methodology suggested by the GUM (ref. *3*) and other specialists in uncertainties measurement (ref. *5*).

2.2. The GUM Methodology

Here are the different steps to follow (ref. *3*and ref. *5*).

1. **Specify the equation**

   Y = f(X1, X2,...Xn)

2. **Identify and characterize the uncertainty sources**
   What are the Xi uncertainties, what could be the reasons for them to vary (environmental parameter (T°), load...). Locate in the end of the paper, sources that are common to all measurements are discussed (repeatability/reproducibility uncertainty, ...)

3. **Quantify the Magnitude of Uncertainty Components** Based on observation (Type A) or datasheets (Type B)

4. **Convert Uncertainty Components to Standard Deviation Equivalents**
   An accuracy given in a datasheet must be correctly converted in a standard deviation equivalent. A given accuracy based on a gaussian distribution or a rectangular distribution will lead to different standard deviation. The standard deviation equivalent corresponds to the uncertainty for a 68,27% confidence interval.

5. **Compute the Combined Standard Uncertainty**
   Once all the uncertainties are found, we combine them following the root sum of squares method (RSS)

6. **Compute the Expanded Uncertainty**
   Once the combined uncertainty is found, we can express the final uncertainty as a probability of belonging to an interval. Usually, a confidence interval of 95% is constructed. The reason is that all calibration reports and datasheets usually given the uncertainty for this confidence interval. In this report, the confidence uncertainty will be given for $\mathbf{1\sigma, 2\sigma, 3\sigma}$.

Usually, an accuracy is always given for a confidence interval. What does it mean exactly?
For instance, when a manufacturer produces a set of identical products, the features of these may vary from one to another. As an example, if we try to manufacture a set of 100Ω resistors, the resistor values may follow a normal distribution around 100Ω.

So, from that point we can make confidence intervals around 100 Ω. An 95% confidence interval is common for example. In our case, an example of 95% confidence interval could be: [99, 101] Ω.
First, we can say that there is a specific uncertainty (1 Ω in our example). This uncertainty is based on all the resistor values measured after manufacturing. In short, if we take a random resistor, it means that we will have a 95% chance to have that resistance value contained in this 95% confidence interval.

2.3. The GUM applied in our measurement system

The following part will detail how the uncertainties in our measurement system are found using this methodology. At first, we will base our analysis on data given by the manufacturers like datasheets. This analysis is called Type B analysis. After that, we will make our own measurements to perform a Type A analysis.
The calculation of uncertainties is in fact a statistical process aimed at determining the range within which the true value of the measurement is likely to lie. Uncertainty reflects the inherent limitations of any measurement process and manifests in two primary forms:

- **Type A Uncertainty**: Determined through statistical analysis of repeated measurements within the experimental setup, yielding a confidence interval that quantifies precision and variability.
- **Type B Uncertainty**: This class of uncertainty is derived from sources outside our direct experimental measurements. It encompasses information such as manufacturer specifications, historical data, and past experiments.

As said before, the MEMS can be powered using either a voltage source, or a current source. The uncertainty must be computed for both cases.
Also, for the reference pressure sensor and the reference temperature sensor *PT1000*, both have an uncertainty that must be computed.
Once we have all these uncertainties, we compute the uncertainty on the pressure we measure using a MEMS as well as the temperature, measured by the equivalent resistor[1].

We can always write:

$$\frac{\textit{The uncertainty on the measurand}}{\textit{The measured value}}.100 = \%\ \textit{uncertainty on the measured value}$$

In this relation, the absolute uncertainty (the uncertainty on the measurand) is converted into a relative uncertainty that is relevant for any measurement.

2.4. An example – The PT1000

The circuit can be defined as on Figure 5.

[1] Our sensors are also able to measure the temperature using the thermal sensitivity of our Wheatstone bridge resistor.

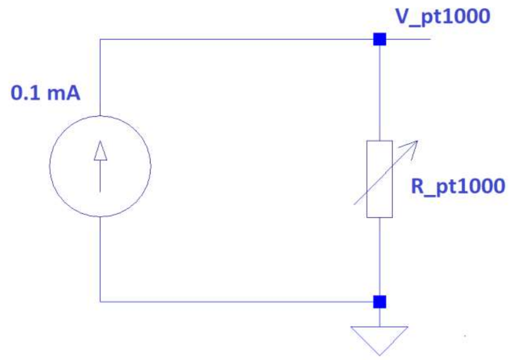

Figure 5- Temperature measurement using the PT1000

Identifying and characterizing uncertainty sources based on datasheets (Type B), we can find with some developments the components uncertainties at 2σ as summarized in Table 1.

Uncertainty component	Uncertainty source	Relative Standard deviation (2σ)	Distribution	Degree of freedom
I	Tolerance	0.091%	Normal	∞
V_{pt1000}	Acquisition	0.08%	Normal	∞
	Resolution	0.005%	Rectangular	∞

Table 1 - Combined standard uncertainties for the temperature measurement

We can then write the following:

$$\frac{\Delta R_{pt1000}}{R_{pt1000}} = \left(\left(\frac{\Delta I}{I}\right)^2 + \left(\frac{\Delta V_{pt1000}}{V_{pt1000}}\right)^2\right)^{0.5}$$

$$\frac{\Delta R_{pt1000}}{R_{pt1000}} = \left((0.091\%)^2 + (0.08\%)^2 + (0.005\%)^2\right)^{0.5} \sim 0.121\%$$

The combined uncertainty for R_{pt1000} is 0.121% with a 95.4% confidence interval when performing a type B uncertainty computation. These uncertainties are useful to determine the uncertainty on the temperature. Indeed, the formula to get the temperature is**:**

$R_{pt1000} = R0*(1+\alpha T+\beta T^2)$, **where** $R0, \alpha, \beta$ **are constant.**

By considering uncertainty formulas given by the PT1000 manufacturer and calibration done by the sensor manufacturer on the PT1000, we can obtain the extended (or expanded) uncertainty for the temperature value (Table 2 and 3).

Confidence interval	1σ	2σ	3σ
R_{pt1000}	0.66 Ω(0.060%)	1.32 Ω(0.121%)	1.98 Ω(0. 18%)
Temperature	0.17°C (0.68 %)	0.34°C (1.36%)	0.51°C (2.04%)

Table 2 - Temperature measurement uncertainty at 25°C

Confidence interval	1σ	2σ	3σ
R_{pt1000}	1.06 Ω(0.060%)	2.12 Ω(0.121%)	3.18 Ω(0. 180%)
Temperature	0.27°C (0.135 %)	0.54°C (0.27%)	0.81°C (0.40%)

3 - Temperature measurement uncertainty at 200°C

The change from a temperature to another is the value of the PT1000 resistor. The higher the temperature, the higher the resistor value. The higher the resistor value, the higher the resistor uncertainty. That is why the uncertainty at 200°C is higher than the one at 25°C.

3. Results of MEMS pressure measurement uncertainty

The following part will discuss about the Uncertainty calculate of MEMS pressure measurement in the range 0-2bar.

The general formula to obtain the pressure is:

$$P = \frac{s^+ - s^-}{V^+ - V^-} * s(T) + b(T)$$

with s the MEMS sensitivity and b the offset. This formula allows to determine the pressure based on the output signals of the MEMS.

3.1. The linear regression law

The linear regression law plays a crucial role in modelling the transfer function of sensors. This transfer function is the equation that relates the sensor's output to the measured quantity (here P).

- **Formulation of Linear Regression**: The simplest form is y=ax+b, where y is the sensor output, x is the measured quantity, a is the slope of the line (sensor sensitivity), and b is the y-intercept (sensor offset).
- **Application of Linear Regression**: In practice, the method of least squares is often used to find the optimal values of a and b that minimize the differences between the measured values and those predicted by the linear model. This allows for accurate characterization of the sensor's response.

3.2. The connection between linear regression and sensor accuracy

Linear regression, also called the Best Fitted Straight Line (BFSL) is intrinsically linked to sensor accuracy. By determining the sensor's transfer function, linear regression helps identify and correct systematic deviations that might affect accuracy. For instance, the slope (a) and intercept (b) of the linear transfer function reveal how the sensor's response proportionally varies with respect to the measured quantity and its potential bias.

Accurate adjustment of these parameters through linear regression ensures that the sensor responds consistently and predictably, which is vital for accurate measurement. Furthermore, the analysis of residuals – the differences between the measured values and those predicted by the regression model – provides critical insight into the sensor's random variability, another key component of accuracy. In summary, linear regression does not just model the relationship between the sensor output and the measured variable; it also plays a fundamental role in optimizing and validating the sensor's accuracy.

The BFSL is also a good mean to allow the final user of the sensor, to implement this equation to its own test bench[2]. Of course, additionally to that the end-user has to make the full uncertainty calculation taking into account its own chain of measurements.

3.3. Combined standard uncertainty computation

This example could look very complex, in fact it is relatively simple but need to be very exhaustive and must be done for every sensor having different range of measurement because the chain of measurements will be affected.

The measurement of each output of the MEMS generates uncertainty. All these uncertainties must be combined.
The combined standard uncertainty of the measurements on S and on V depends on the source used (current or voltage). Table 4 summarizes the uncertainty at $2\boldsymbol{\sigma}$ in the range 0 – 2 bar for our test bench.

	Uncertainty component	Uncertainty source	Relative Standard deviation	Distribution	Degree of freedom
Voltage Source	$(S^+ - S^-)$	Acquisition	0.18%	Normal	∞
		Resolution	0.01%	Rectangular	∞
	$V^+ - V^-$	Acquisition	0.03%	Normal	∞ ∞
		Resolution	0.003%	Rectangular	
	Regression	Regression	TBD	t-student	TBD
Current source	$(S^+ - S^-)$	Acquisition	0.29%	Normal	∞
		Resolution	0.02%	Rectangular	∞
	$V^+ - V^-$	Acquisition	0.05%	Normal	∞ ∞
		Resolution	0.005%	Rectangular	
	Regression	Regression	TBD	t-student	TBD

Table 4 - Pressure MEMS uncertainties

The regression uncertainty is highly dependent on the sensor itself since those sensors will all have their own regression with slightly different parameters. They have been left as "to be determined" in Table 4 but section 3.5 gives a specific example illustrating the incorporation of regression uncertainty into the analysis.

3.4. Quantitative Illustration: Calculation Methodology

[2] Remember, that 50 to 80 %, of the uncertainty is coming from the test bench.

Considering the example of a voltage source application (5 V), we can write the following:

$$\frac{\partial P}{\partial V} = = s * (s^+ - s^-) * \frac{-1}{(V^+)\hat{}2} = \frac{50.10^{-3}}{0.01}\frac{-1}{25} = -200\ mbar/V$$

$$\frac{\partial P}{\partial (s^+ - s^-)} = \frac{s}{V^+} = \frac{1}{0.01*5} = 20\ mbar/mV$$

$$\frac{\partial P}{\partial s} = = \frac{s^+ - s^-}{V^+} * s = 100\,000\ V.mbar^2/mV$$

$$\frac{\partial P}{\partial b} = 1$$

and finally, to total uncertainty u_c :

$$u_c^2 = (supply)^2 + (differential\ voltage)^2 + (linear\ regression)^2$$

With as values for the supply and differential voltage terms:

$$(supply)^2 = \left(200 * \frac{0.03}{100} * 5\right)^2 = (0.3)^2$$

$$(differential\ voltage)^2 = \left(20 * \frac{0.18}{100} * 50\right)^2 = 1.8^2$$

We observe that the differential voltage will dominate the uncertainty. Since we are only interested in the bench uncertainty, we will not take the regression uncertainty into account for this discussion.

Figure 6 and Figure 7 give the uncertainty on the measured pressure in function of the pressure following type B GUM methodology using respectively a voltage source and a current source.

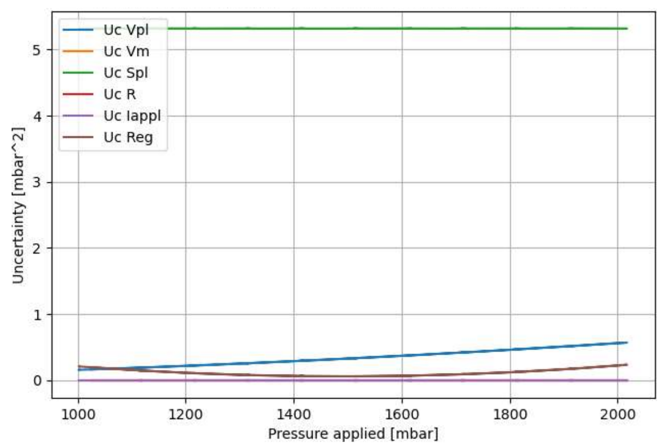

Figure 6 - Pressure uncertainty in function of the applied pressure (voltage source) (at 25°C)

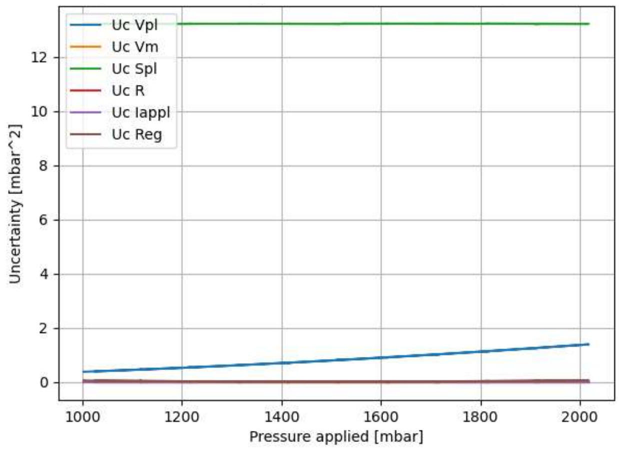

Figure 7 - Pressure uncertainty in function of the applied pressure (current source) (at 25°C)

The legend for the curves in the figures is as follows:

- Uc Vpl: Contribution to pressure uncertainty from V+
- Uc Vm: Contribution to pressure uncertainty from V-
- Uc Spl: Contribution to pressure uncertainty from S+
- Uc R: Contribution to pressure uncertainty from the bridge resistor
- Uc Iappl: Contribution to pressure uncertainty from the current applied to the MEMS
  Uc Reg: Contribution to pressure uncertainty from linear regression

As an example, with a voltage source, we can compute an extended uncertainty. We can state that the uncertainty for the measured pressure *P* is:

1. 0.91 mbar with a 68,3% confidence interval or 1σ
2. 1.82 mbar with a 95,4% confidence interval or 2σ
3. 2.74 mbar with a 99,7% confidence interval or 3σ.
4. Remark: It means that, commercially speaking we could claim an accuracy for our sensor of 0.91 mbar/2000mbar = 0.0455% saying that a part of this number is coming from our test bench. But of course, it is not correct to put such kind of technical information. Indeed, I take the information for 1σ and for a fixed temperature (25 Celsius in this case) which is of course never the case. In SENSORADE's datasheet, we are usually claimed 0.5%, so ten times higher, knowing that we are more accurate than that.

3.5. Test bench uncertainty contribution

To assess the impact of the calibration bench on the overall uncertainty, we employed the following methodology. Initially, we conducted a standard calibration, considering various sources of uncertainty outlined in the preceding section. Subsequently, we substituted the acquired data associated with the sensor's output with data from a hypothetical 'ideal' sensor. These data points were generated by applying the inverse relationship derived from the general linear transfer function of a pressure sensor:

$$S = \frac{P - b}{a}$$

Here S represents the output of the hypothetical sensor, P denotes the reference pressure, *a* being the chosen slope and *b* the chosen intercept.
This approach was applied to a sensor with a range of 100 psi and a diameter of 1.2 mm, yielding the results presented on Table 5 and Table 6.

S [V]	Pref [mb]	Ppred [mb]	$\sigma 1$ [mb]	$\sigma 2$ [mb]	$\sigma 3$ [mb]
-0.015	1000.606	1013.864	5.142	10.98	17.294
-0.01	1490.451	1480.883	4.815	10.195	15.967
-0.003	1990.419	1984.135	4.523	9.487	14.76
0.003	2490.53	2487.715	4.303	8.948	13.836
0.009	2990.164	2988.113	4.168	8.613	13.258
0.015	3490.104	3492.444	4.123	8.502	13.065
0.022	3989.552	3991.539	4.174	8.625	13.275
0.028	4488.928	4491.873	4.315	8.971	13.868
0.034	4988.938	4991.882	4.538	9.514	14.798
0.04	5489.294	5491.763	4.832	10.225	16.006
0.046	5988.663	5983.439	5.178	11.055	17.408

Table 5 - Uncertainty computation for the real sensor

S [V]	Pref [mb]	Ppred [mb]	$\sigma 1$ [mb]	$\sigma 2$ [mb]	$\sigma 3$ [mb]
-0.016	1000.606	999.971	3.543	7.087	10.633
-0.01	1490.451	1490.642	3.537	7.074	10.613
-0.003	1990.419	1990.596	3.534	7.07	10.606
0.003	2490.53	2490.702	3.534	7.068	10.604
0.009	2990.164	2990.32	3.535	7.071	10.607
0.016	3490.104	3490.24	3.538	7.077	10.616
0.022	3989.552	3989.644	3.543	7.086	10.63
0.029	4488.928	4488.966	3.549	7.099	10.65
0.035	4988.938	4988.907	3.557	7.116	10.675
0.041	5489.294	5489.259	3.567	7.136	10.705
0.048	5988.663	5988.402	3.579	7.159	10.741

Table 6 - Uncertainty computation for the ideal sensor

With S being the output voltage of the sensor, Pref the reference pressure, Ppred the predicted value using the regression and finally the associated total uncertainties for 1**σ**, 2**σ**, 3**σ**.
As anticipated, the regression uncertainty is now nearly negligible, and the primary contributor to the uncertainty in Table 6 is the variability in acquiring the output of the sensor. Since this contributor depends solely on the calibration bench and remains consistent between tests with the real and ideal sensors, we can infer that the sensor's uncertainty is encapsulated in the regression uncertainty. Notably, the calibration bench also exerts an influence on the regression uncertainty.
Given this understanding, we reasonably estimate that the calibration bench contributes at least 50% to the total uncertainty. In cases involving less sensitive sensors and with tighter control over calibration parameters, we can further reduce regression uncertainty, resulting in up to 80% of uncertainty attributed to the test bench in certain scenarios.

3.6. Type A GUM methodology - How to improve accuracy?

To be more accurate, instead of using datasheet data, we can measure the uncertainty through data measurements or so-called "observations". This is then using the Type A GUM methodology.
We need to acquire a set of data using a data acquisition device. In our case, we used a device Fluke 8846A (ref. *6*). The number of samples is noted N. The degree of freedom, v, is equal to v= N-1. The procedure is as follows:

1. Take the mean value of **the data**: µ
2. Compute the standard deviation of **the data**: σ
3. Compute the uncertainty of µ, σ_{μ}, using the formula:

$$\sigma_{\mu} = \frac{\sigma}{\sqrt{N}}$$

An excellent illustration of this methodology can be found in ref. 7(pages 31-36).
In fact, what we do, we calibrate, each time it is possible, all elements lying in the measurement chain.

3.7. Reproducibility uncertainty

Another source of uncertainty could be the reproducibility uncertainty. To test it, we follow the same procedure as for the repeatability uncertainty, but instead of acquiring all the data in one day, we perform it over a few days. Indeed, the uncertainty on the uncertainty method must be judged. By attempting only one series of measurements to state a type A uncertainty, we do not assure that the system will react the same way next time.

Temperature measurement uncertainty

The temperature could introduce uncertainties in pressure measurement. As depicted in the section 4.3, this issue has been overcome by basing the linear regression equation on the resistor bridge value.

However, given that the Sensorade sensor can also work as a temperature sensor, it is imperative that temperature measurements are accurate. The uncertainty of temperature measurement arises particularly because of the spatial separation between the temperature and pressure sensors, which may result in the temperature sensor not accurately capturing the temperature experienced by the pressure sensor. The illustration in Figure 8 demonstrates this issue, showing how four temperature sensors positioned between two heaters record different temperatures due to their spatial separation.

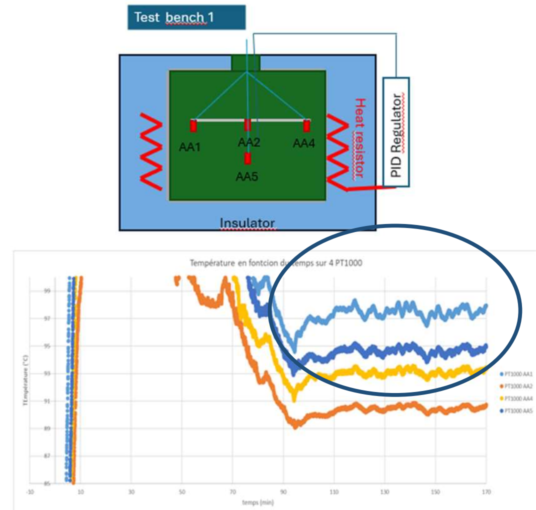

Figure 8 - Discrepancy in measurement of four PT1000 placed between to heater

To mitigate this issue, the Sensorade test bench is designed with an oven to enhance temperature uniformity throughout the test environment as depicted in Figure 9.

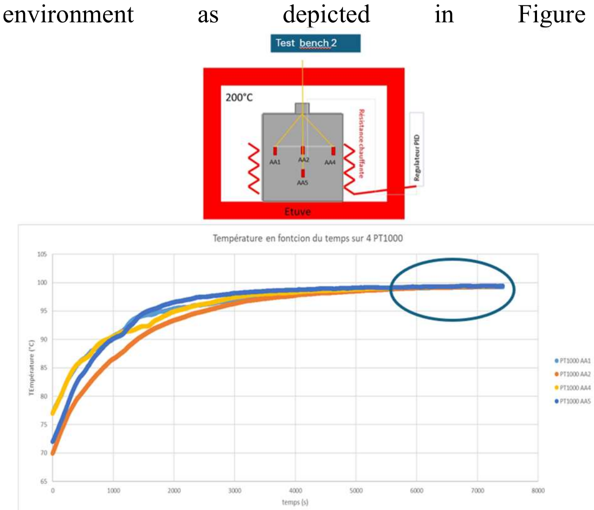

Figure 9 - Discrepancy in measurement of four PT1000 place between to heater in an oven

The establishment of a linear regression equation between the temperature and the bridge resistance of the MEMS based on the setup depicted in Figure 9, increase the accuracy of the measurement. This allows the direct measurement of temperature via the resistor bridge, effectively eliminating the need for an external temperature sensor. This approach is more accurate than using an external temperature sensor (even if this one is "on paper" very accurate), which obviously introduces more uncertainty due to its greater distance from the measurement point. In fact, in that last case, you probably would not trust the external temperature measurement.

4. Factor of influences on ultraminiaturized pressure sensor

When you need to ensure a level of accuracy/uncertainty of sensor a lot of parameters have to be considered. Indeed, now you can make the calculation itself, but you need to know why a sensor is accurate or not whatever the acquisition system used. For ultra miniaturized sensor is the ultimate difficulty. Indeed, even the way you assemble a piezoelectric MEMS[3] it could create inaccuracy effect.

4.1. Effect of packaging on accuracy

Understanding the concept of packaging is essential in this context. In the semiconductor field, packaging encompasses all the techniques used to electrically connect semiconductor components, safeguard them against environmental factors, and ensure the component's usability and testability. For ultraminiaturized sensors, critical assembly techniques include:

- Glueing/attaching the MEMS on a substrate (we call it die attach)
- Wirebonding of the MEMS to ensure the electrical connection (see Figure 10)

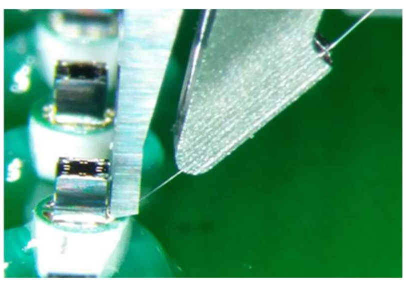

Figure 10 - Wire bonding of the MEMS on a substrate having 1.2mm of diameter Do the encapsulation of the wirebonds without touching the membrane

- Adding wiring manageable by an operator (Figure 11)

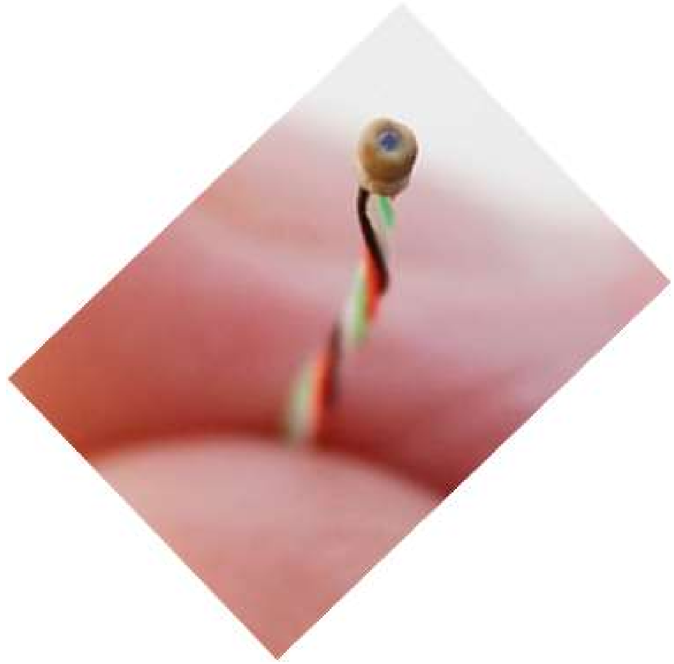

Figure 11 - Pressure sensor of 1.2 mm diameter

These procedures are vital for the integrity and functionality of the sensor. However, they can also be sources of stress and inaccuracies. For example, when observing a fully assembled absolute MEMS sensor, it might appear that the membrane is unstressed due to the surrounding silicon's freedom to move. In reality, the adhesive can stress the membrane, leading to offset values that vary with pressure and temperature. This is because the substrate, adhesive and MEMS have different coefficients of thermal expansion, this leads to stress the membrane and directly affect accuracy.

The assembly shown in Figure 12Figure 11 represents the best method for a given MEMS to obtain a very accurate measurement but is notably fragile and susceptible to humidity and potentially leading to short circuits or loss of electrical connection. This indicates that while the method enhances accuracy, it may compromise the sensor's durability and robustness.

[3] In this example, the analogic pressure sensor is using a piezoelectric MEMS as the sensitive element.

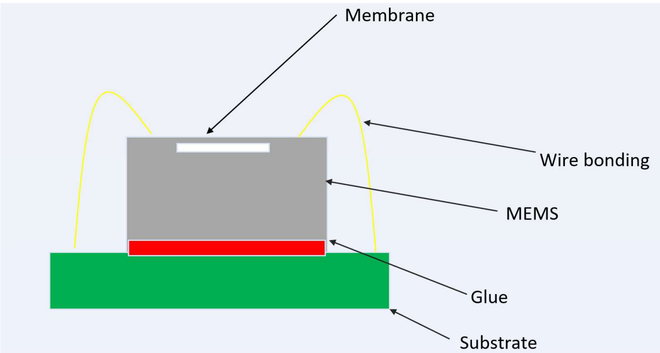

Figure 12 - MEMS glued & wirebonded on the substrate

To maintain high accuracy levels, especially with encapsulation methods as shown in Figure 13, selecting the most effective encapsulation technique is crucial. As shown later on, comparative tests at 1013 mbar across temperature cycles from room temperature to 185 Celsius demonstrate the impact of encapsulation on accuracy, particularly in the form of an hysteresis between 90 to 130 Celsius, attributable to the adhesive or a combination of the adhesive and encapsulation.

To maintain an exceptionally high level of accuracy, especially when employing an encapsulation method as illustrated in Figure 13, it is imperative to carefully choose the most optimal encapsulation available.

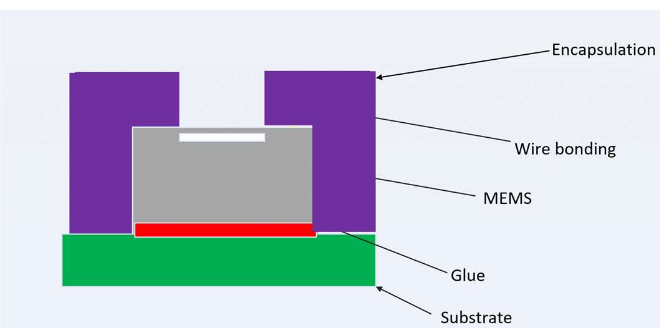

Figure 13 - MEMS glued, wirebonded & encapsulated on the substrate

Figure 14 shows the test comparison @ 1013 mbar during a temperature cycle from room temperature till 185 Celsius. You can observe a test made first without encapsulation and after with encapsulation on the sensor tested without encapsulation.
These observations underscore the importance of assembly techniques in influencing the precision of ultraminiaturized pressure sensors. Despite focusing on the effects of encapsulation and intentionally using a suboptimal encapsulation to highlight its impact, extensive research and testing have been conducted to mitigate these effects, aiming to achieve results comparable to those without encapsulation.
We have converted the variation of the offset express in mbar. The main variation is coming from the sensitivity of our sensor with temperature (which is expected and needed), but anyway, you can see, in the range from 90 to 130 Celsius, an hysteresis. This hysteresis is coming from the glue or from the glue and the encapsulation.

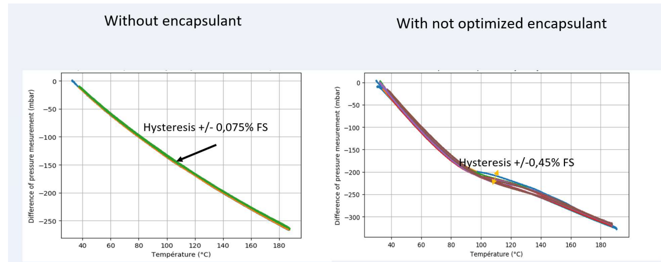

Figure 14 - Effect on the encapsulation on accuracy

These observations underscore the importance of assembly techniques in influencing the precision of ultraminiaturized pressure sensors. Despite focusing on the effects of encapsulation and intentionally using a suboptimal encapsulation to highlight its impact, extensive research and testing have been conducted to mitigate these effects, aiming to achieve results comparable to those without encapsulation.

4.2. Natural Frequency

The natural frequency of the MEMS significantly impacts the accuracy of measurements. Primarily, it dictates the maximum frequency at which dynamic measurements can be conducted effectively (usually 5 times lower than the natural frequency). If the frequency of the measurement is too close to the natural frequency of the MEMS, the MEMS' membrane will be unable to track the pressure variation which leading, inevitably, to a unrealistic measurement.
Moreover, measurement accuracy can be compromised if an external excitation resonates at the same frequency as the MEMS's natural frequency. Such resonance within the MEMS membrane may induce unmanageable vibrations on the membrane.

This phenomenon can be mitigated by using MEMS with a high resonance frequency. An example of this is the Sensorade sensor, which has a natural frequency of 2.675 MHz, as depicted in Figure 15.

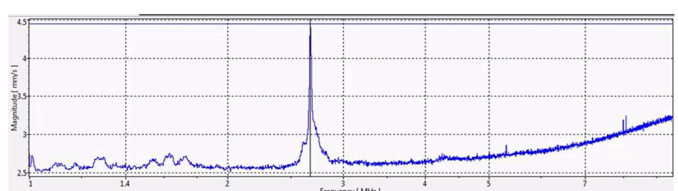

Figure 15 - Graphic of the magnitude (mm/s) of the MEMS and the frequency (MHz)

It is crucial to acknowledge that this phenomenon affects every part of the sensor. For instance, in one Sensorade sensor model, the MEMS is encased within a tube. In such a setup, the resonance of the tube becomes as significant as the one of the MEMS itself. Figure 16 illustrates the variance in frequency resonance between a tube that is fully embedded and one that is partially embedded, revealing a drastic alteration in the resonance frequency. It must be understood that a bad embedding of the tube will lead to a non-understandable measurement.

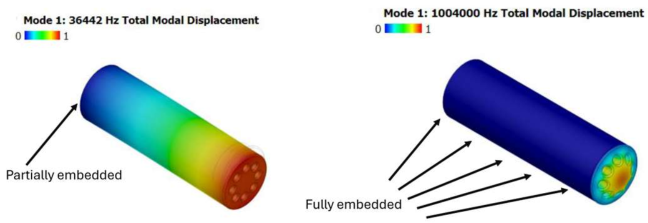

Figure 16 - Natural frequency of partially and fully embedded tube

4.3. Temperature

Temperature will invariably influence the precision of the measurement, given that the measurement technique relies on a resistor bridge, and the resistance values will vary with temperature changes. Such variations in resistance can significantly alter the differential voltage measured. Consequently, even at a constant pressure, the MEMS measurement will fluctuate with temperature, directly affecting the accuracy of the measurement. Figure 17 illustrates how, for the same sensor, the linear relationship between the pressure and the measured voltage shifts with temperature changes.

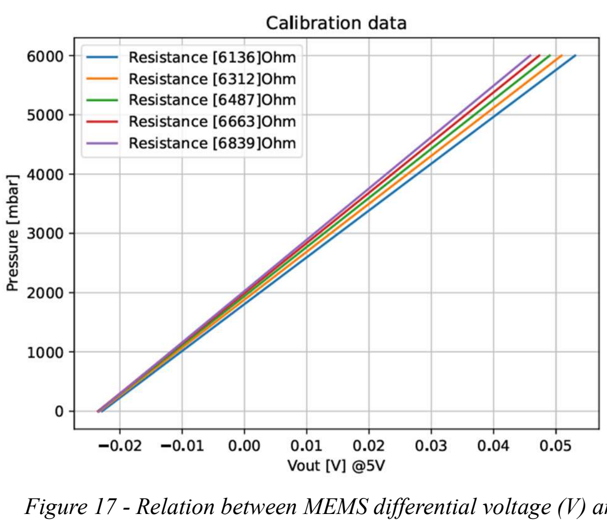

Figure 17 - Relation between MEMS differential voltage (V) and pressure (mbar) for different temperatures

However, this phenomenon has been overcome by the establishment of a linear regression (based on the calibration) that links pressure, differential voltage measure and resistor bridge value. When basing the equation on the resistor bridge value (instead of temperature), pressure measurements are rendered entirely independent of temperature variations.

4.4. Radiation

Light radiation, as well as temperature, can impact the accuracy of measurements. Given the MEMS membrane's thin and small nature, light radiation can easily heat the membrane, affecting the bridge resistor value and, consequently, the measurement. Few experiments conducted on a sensor under constant pressure and temperature conditions have demonstrated that measurements vary with the exposure of the MEMS to light. This fluctuation poses a challenge when seeking high measurement accuracy.

Based on the same method as described in section 4.3, this problem has been resolved. By basing the linear regression equation on the resistor bridge value, the impact of light on the measurements has been overcome.

4.5. EMC noise

EMC (Electromagnetic Compatibility) noise is a significant concern. By definition an electrical noise is any unwanted variation in voltage or current that is typically random, often of relatively low amplitude, and always undesirable.
Such variations can pose a substantial problem, especially since the pressure measurement is directly linked to the differential voltage measurement. Unwanted fluctuations in this voltage can compromise the accuracy of the measurement.
one of the main sources of the noise is usually the EMC (i.e., a big electrical generator close to the test bench).
However, it is possible to enhance the sensor's immunity to such noise. This can be achieved through measures such as shielding the cables connected to the sensor, minimizing cable lengths, or even shielding the sensor itself, if feasible.

5. Static versus dynamic measurements

Static calibration and dynamic calibration are two different methods used to ensure the accuracy and reliability of measurement instruments. Static calibration involves comparing the output of a measurement instrument to a known standard or reference value while the instrument is not in motion. This helps to determine the instrument's accuracy and precision under static or stationary conditions.
Dynamic calibration, on the other hand, involves assessing the performance of a measurement instrument while it is in motion or while measuring dynamic processes, thus not well stabilized working conditions. This type of calibration is particularly important for instruments used in applications where measurements are taken during movement or changes in conditions, as in the case of this pressure sensor. Both static and dynamic calibration are essential for ensuring that measurement

instruments provide accurate and reliable data in various real-world scenarios.
Dynamic calibration has reference values that change with time and you measure the response of the sensor as it also changes with time. For example, you measure a pressure sensor response at 200 mbar and keep measuring until it is exposed to 500 mbar, so you end up with a graph, and not just data points.

6. Conclusions

In this paper, we obtained the uncertainty associated to all the measurements made using the pressure sensor data acquisition board during well stabilized thermodynamic conditions. To do so, we followed a reference guide: *Evaluation of measurement data —**G**uide to the expression of **u**ncertainty in **m**easurement,* or the GUM (ref. *3*). The methodology explained in the GUM suggests two main approaches:

1. Type A uncertainty. This is based on measurement and data gathering. Then, with the help of statistics, uncertainties can be derived.
2. Type B uncertainty. This is based on reference documents like calibration report, datasheet, etc., where the uncertainties are already available.

We first followed a type B methodology. Then, to reduce the uncertainty, the type A methodology has also been introduced. It is based on measurements and allowed to reduce sources uncertainties.
We also show the various factors that influence sensor accuracy and the many precautions that need to be taken.

In conclusion, it is important to acknowledge that a significant portion, ranging from 50% to 80%, of uncertainty stems from the test bench under fixed or well-established thermodynamic conditions. However, real-world scenarios often involve the measurement of specific events, where environmental factors can rapidly fluctuate. Thus, meticulous analysis of results becomes imperative. The employment of the BFSL technique proves invaluable in enhancing the accuracy and reliability of measurements under such dynamic conditions.

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