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A Study on Improving Pressure Sensor Calibration Based on Multiple Calibration Points and Auto Target Setting*

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Abstract

Pressure sensors are essential equipment for precise measurements in industrial and research fields, requiring calibration and target value setting for each sample to ensure high accuracy. This study proposes an automated target value prediction method based on a polynomial regression model to enhance pressure sensor accuracy and evaluates its effectiveness. Experiments were conducted over a pressure range of 0 to 45 bar and a temperature range of -5°C to 60°C. By expanding the calibration points from the previous two to four, linearity error was improved from 0.380% to 0.116%. In the conventional method, theoretical output values were manually calculated based on LDO voltage, and target values were set accordingly. However, this study employed a method that uses Polynomial Features (degree=2) transformation followed by a Linear Regression model to automatically predict target values. This approach allowed samples to more precisely follow the target voltage. This study demonstrates that an automated target value setting with multiple calibration points can contribute to improving the accuracy of pressure sensor measurements.

Keywords : Pressure sensors, Calibration, Auto target, Points, LDO, Linear Regression

JEL Classification Code : L62, L86

1. Introduction

Pressure sensors are widely used in modern industry and research for various applications, and accurate, stable pressure measurement is essential to ensure system performance and safety. However, inaccuracies during the calibration and alignment processes can negatively impact not only measurement accuracy but also the consistency of output values across multiple samples, potentially leading to decreased system reliability and overall performance degradation. Moreover, sensors may struggle to deliver accurate and consistent measurement results under varying environmental conditions (Tengis et al. 2024). Therefore, the process of calibrating sensors so that their output values consistently match target values is a critical research topic (Chen et al., 2019).

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This paper proposes calibration and alignment methods to improve pressure sensor measurement accuracy and maintain output consistency across samples. In particular, this paper focused on alignment based on UDR (Universal Digital Readout) output values derived from LDO (Low Dropout Regulator) output values, rather than physical positioning adjustments. The UDR output values vary for each sample and are influenced by the LDO output values. Leveraging this characteristic, the calibration process was performed to ensure that the UDR output values of all samples within the pressure range accurately correspond to the target pressure values.

The experiments in this paper were conducted within a pressure range of 0 bar to 45 bar and a temperature range of -5℃ to 60℃. Initially, calibration was performed using two pressure and temperature points, but this was later expanded to four points. As a result, the linearity error was significantly improved from 0.380% to 0.116%, and the consistency of UDR output values across samples was enhanced.

In conventional methods, such as using LDO voltage-based theoretical calculations, target values were set manually for each sample, which limited accuracy and efficiency in maintaining consistent output across varying conditions. To improve this, the paper introduced a polynomial regression model to automatically predict target values. By utilizing Polynomial Features (degree = 2) and the Linear Regression model to transform and analyze the voltage data, the process was automated to ensure that the UDR output values consistently followed the target voltage values as the LDO output values changed.

This paper suggests the potential for improving the consistency of outputs across samples by improving the calibration and alignment methods based on UDR output values influenced by LDO output values. It also proposes that increasing the number of pressure and temperature points beyond the current four could yield even better results.

2. Literature Review

2.1. Pressure-Temp Data Collection

In order to accurately measure and collect pressure and temperature data, a pressure sensor, a PTC (Positive Temperature Coefficient) temperature sensor, and an SSC (Sensor Signal Conditioner) chip capable of collecting and processing sensor data are essential. Conventional industrial pressure sensors were unsuitable for our system due to size and cost constraints, so we selected the KELLER Series 10L MEMS pressure sensor, which offered compact size and high precision suitable for our application. This sensor is compact yet offers high precision, and it is capable of reliably measuring pressure in various environments.

For temperature measurement, we used a PTC sensor. The PTC sensor has a characteristic where its resistance changes with temperature, enabling accurate detection of temperatures in the range of -5℃ to 60℃. This feature not only enhances the reliability of the entire measurement system but also contributes effectively to temperature calibration.

Traditionally, analog signal processing systems have been used to process pressure and temperature data, but such systems are susceptible to noise and struggle to maintain accuracy. Therefore, we employed the ZSSC4151C SSC chip to convert the analog signals collected from the MEMS pressure sensor and PTC temperature sensor into digital signals. This chip not only converts analog signals into digital form but also supports functions such as signal amplification, calibration, and stable transmission of sensor data.

Figure 1 presents the ZSSC4151C block diagram, showing connections between the pressure and temperature sensors and the chip, where analog signals are converted to digital form. Additionally, it shows that the chip supports various interfaces and functions, playing a crucial role in enhancing the accuracy and reliability of the sensor data.

The pressure sensor PCB we designed is equipped with the KELLER Series 10L MEMS pressure sensor and the PTC temperature sensor, with the ZSSC4151C chip located at the center, collecting and processing data from the sensors. This sensor module is designed to accurately collect and digitize pressure and temperature data, which is then transmitted to a microcontroller.

Through this configuration, we were able to collect pressure and temperature data stably and consistently across various environmental conditions.

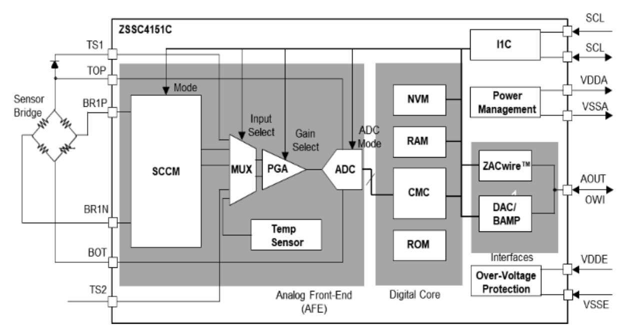


Figure 1: Block Diagram of the ZSSC4151C

2.2. Polynomial Regression-Based Model

A second-degree polynomial regression model was employed in the calibration process of pressure sensors to accurately represent the nonlinear relationship between voltage data and target output values. Polynomial regression, used in machine learning and statistics, is a statistical method that leverages the relationships among two or more quantitative variables to predict one variable based on others (Park, 2016). By defining the form of a polynomial function in advance and using the least squares method to determine the regression coefficients, polynomial regression provides a straightforward way to model data. This approach is advantageous due to its conceptual simplicity and ease of numerical calculation (Park et al., 2013). Through polynomial regression, nonlinear relationships between data can be modeled (Kwak et al., 2024). As such, the polynomial regression model is an extended form of linear regression, capable of effectively modeling complex nonlinear relationships between inputs and outputs by incorporating polynomial terms of the input variables. In this study, voltage data was collected under various pressure and temperature conditions using a DAQ (Data Acquisition) device. The collected voltage data was digitized based on UDR (Universal Digital Readout) values from the SSC (Sensor Signal Conditioner) chip. The UDR is the maximum output value that can be provided by the SSC chip and represents the digital value converted from the analog signal measured by the pressure sensor. This data was then compared with the target output values during the calibration process and used as training data for the polynomial regression model.

The second-degree polynomial regression model includes not only the first-degree term of the input voltage data but also the second-degree term, allowing it to accurately capture the nonlinear relationship between the voltage and UDR values. Equation 1 and Figure 2 illustrates the mathematical representation of this polynomial regression model, showing how the input voltage data is transformed into polynomial features and linked to the target UDR values.

The model first takes in the input voltage data, calculates up to the squared terms, and generates the most suitable prediction for the target output value. By doing so, it effectively captures the complex interactions between the voltage and UDR values, which a simple linear model would be unable to explain.

During the training process of the polynomial regression model, the coefficients (β0, β1, β2) are adjusted to minimize the error between the input data and the target output values. The least squares method is used to minimize the error between the predicted and actual target values, thereby building an optimal model. Through this training process, the model learns to accurately predict UDR output values for a wide range of voltage inputs.

$$y = b_0 + b_1 x + b_2 x^2 \tag{1}$$

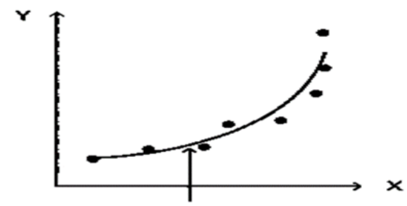


Figure 2: Polynomial Regression Graph

2.3. Related Research

Recent studies on pressure sensor calibration have been actively progressing, with polynomial regression analysis playing a key role in addressing the nonlinearity of pressure sensors. Zou et al. (2023) proposed a method for determining target values suitable for each sample by applying a polynomial regression model based on the output values of pressure sensors. In their study, they achieved improved calibration accuracy by modeling the nonlinear relationships under various pressure conditions.

In line with this, Dikbaş (2024) demonstrated the utility of polynomial regression in forecasting extreme precipitation events, emphasizing its capacity to handle nonlinear data in atmospheric conditions. This approach is relevant to pressure sensor calibration, as it suggests that polynomial regression can also be effective in managing the complexities of sensor outputs under diverse environmental parameters, thereby enhancing predictive accuracy (Dikbaş, 2024).

Additionally, many studies have emphasized that increasing the number of pressure and temperature points is essential for improving sensor calibration effectiveness. These studies clearly demonstrate that both polynomial regression analysis and the increase in calibration points play critical roles in pressure sensor calibration. This study follows the trend of such existing research, aiming to explore methodologies for improving the performance of pressure sensors

3. Research Methods

3.1. Overall Structure

Figure 3 shows the overall system structure. Inside the temperature chamber, the SSC chip and MEMS cell are installed, and the Evaluation Kit communicates with the SSC chip via OWI (One-Wire Interface). Data collection is performed through the Evaluation Kit, which collects pressure data, and the collected data is passed to the data analysis module after calibration. The data analysis module calculates ideal output values based on pressure, reports results after calibration, and calculates linearity. All these processes are controlled through the GUI.

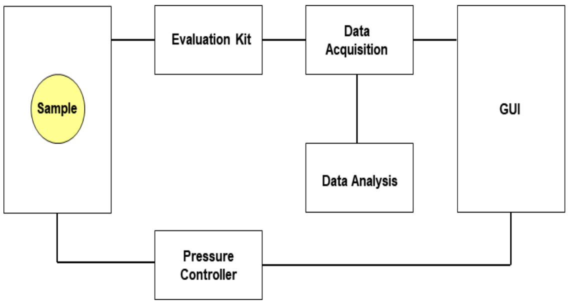


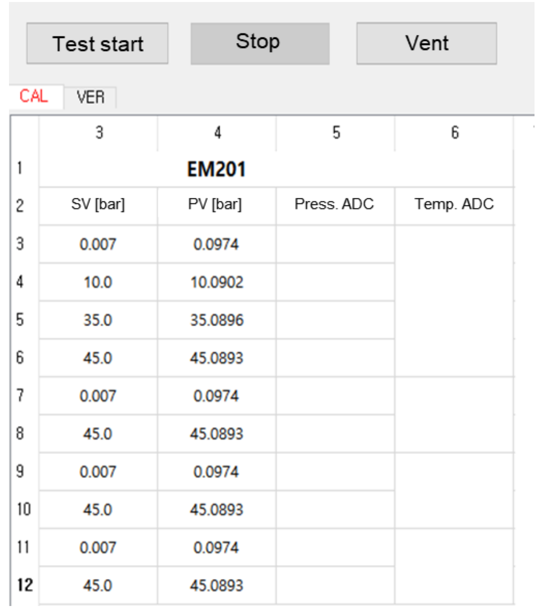
Figure 3: Overall System structure

3.2. GUI

Figure 4 shows the structure of the data collection and results program used in this study. This program has the capability to automatically adjust pressure and temperature according to user-specified pressure and temperature points. Control for obtaining the digital values of the SSC (Sensor Signal Conditioner) chip is performed using software provided by Renesas.

The program, developed in Python, enables efficient data collection and processing using various libraries and modules. After completing calibration at the user-specified temperature and pressure points, the results can be immediately viewed through the program. Notably, the method for automatically predicting target values using the polynomial regression model is also implemented in the GUI. By utilizing the Polynomial Features (degree=2) and Linear Regression models, the voltage data is transformed and analyzed to automate the process of ensuring that the UDR (Universal Digital Readout) output values consistently match the target voltage values as the LDO output changes.

This feature greatly improves system efficiency by enabling users to set experimental conditions and verify calibration results in real time. The program enhances reliability during data collection and reduces the workload for researchers. As a result, pressure sensor calibration tasks can be conducted more precisely and swiftly, playing a crucial role in ensuring the consistency of research outcomes.



	3	4	5	6
1		EM201		
2	SV [bar]	PV [bar]	Press. ADC	Temp. ADC
3	0.007	0.0974		
4	10.0	10.0902		
5	35.0	35.0896		
6	45.0	45.0893		
7	0.007	0.0974		
8	45.0	45.0893		
9	0.007	0.0974		
10	45.0	45.0893		
11	0.007	0.0974		
12	45.0	45.0893		

Figure 4: GUI for Calibration and Verification

3.3. Calibration and Automatic Target Process

In order to achieve accurate calibration of the pressure sensor, data was collected while progressively increasing the number of temperature and pressure points. This was done to improve calibration precision and analyze sensor responses under various environmental conditions. Data collection began with 2 temperature points and 2 pressure points, followed by 2 temperature points with 3 pressure points, and then 2 temperature points with 4 pressure points. Subsequently, data was collected using 3 temperature points with 2, 3, and 4 pressure points, and finally, 4 temperature points with 2, 3, and 4 pressure points, securing a total of 9 different combinations of data.

Although the current technical limitations restrict pressure and temperature points to four, tests with six or eight points are feasible, albeit time-consuming. Additionally, with the current algorithm, increasing from two or four points to six or eight points does not yield significant improvements, indicating a need for deeper research into this area. However, it suggests that adding additional points beyond the current four pressure and temperature points could potentially yield even better results.

Additionally, an automatic target-setting method using UDR (Universal Digital Readout) values was introduced. Based on UDR values, voltage data was acquired, and a polynomial regression model was used to automatically set the target values. A second-degree polynomial was applied using Polynomial Features and Linear Regression to build the regression model, which modeled the nonlinear relationship between the voltage and target values.

Tables 1 and 2 illustrate the calibration digital values according to the number of pressure and temperature points, highlighting the key differences. The remaining tables, which present additional data for various conditions, are provided in the Appendix.

Table 1: 2 temperature points and 2 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
70	0	0.007	0.0974	3050	
	95.36	45.0	45.0893	20302	

Table 2: 4 temperature points and 4 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
10	0	0.007	0.0974	3184	14184
	21.11	10.0	10.0902	7542	
	74.16	35.0	35.0896	18544	
	95.36	45.0	45.0893	22988	
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
40	0	0.007	0.0974	3114	18714
	95.36	45.0	45.0893	21562	
70	0	0.007	0.0974	3050	22640
	95.36	45.0	45.0893	20302	

4. Results and Discussion

4.1. Results

This study presents the measurement results based on the proposed increase in pressure and temperature points. First, the effect of progressively increasing the number of temperature and pressure points on the sensor's linearity was analyzed. Figures 5 and 6 depict the linearity error results for different combinations of temperature and pressure points, with Figure 7 showing the results for 2 temperature points and 2 pressure points, and Figure 8 showing the results for 4 temperature points and 4 pressure points. The remaining figures, which cover additional combinations, are provided in the Appendix. Data collection began with 2 temperature points and 4 pressure points, followed by 3 temperature points and 2, 3, and 4 pressure points, and finally 4 temperature points with 2, 3, and 4 pressure points.

Analysis indicates that sensor linearity gradually decreases as the number of temperature and pressure points increases. The measured linearity values are as follows: 0.380%, 0.367%, 0.285%, 0.274%, 0.144%, 0.095%, 0.308%, 0.166%, and 0.107%. Among these, the combination of 3 temperature points and 4 pressure points showed the lowest linearity error (0.095%). These findings suggest that while both pressure and temperature points influence calibration accuracy, pressure points have a greater impact on improving linearity.

Next, in the automatic target setting section, the results are presented for measurements taken under the same conditions—4 temperature points and 4 pressure points—while changing the samples. The automatic target values were set using a polynomial regression-based model, and the linearity consistency among samples was compared. Figure 7 and 8 shows the changes in automatic target values for each sample. These results demonstrate that the proposed polynomial regression-based automatic target setting method yields similar linearity results even when samples are replaced.

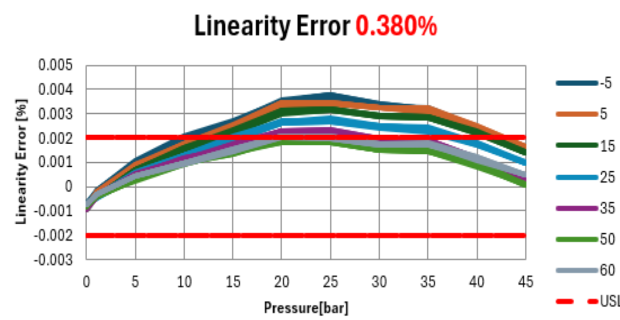


Figure 5: Linearity error of 2 temperature points and 2 pressure points

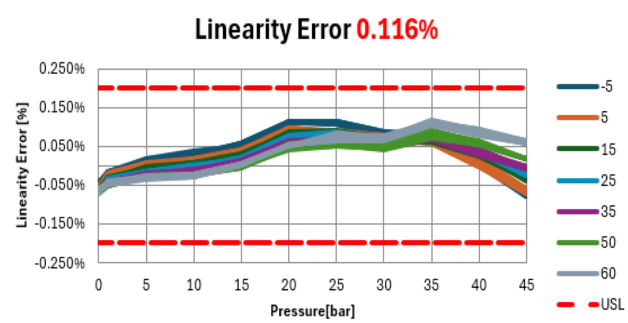


Figure 6: Linearity error of 4 temperature points and 4 pressure points

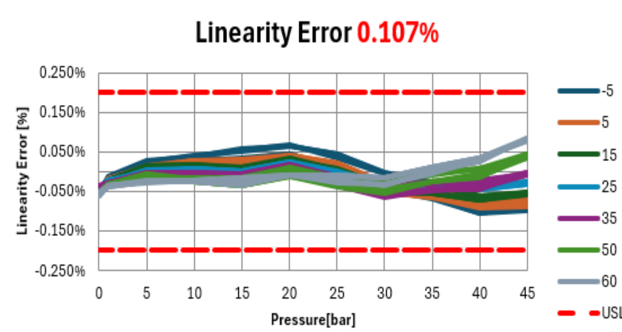


Figure 7: Auto Target Result of Sensor 1

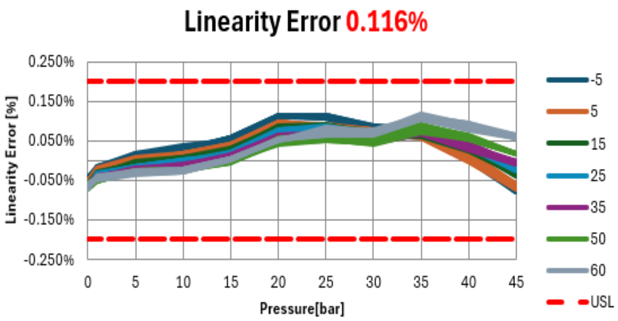


Figure 8: Auto Target Result of Sensor 2

4.2. Discussion

The experimental results from this study confirm that increasing the number of pressure and temperature points affects the calibration accuracy of pressure sensors. In particular, it was found that the number of pressure points has a greater impact on improving linearity than the number of temperature points. This is because the sensor's response to pressure changes is more sensitive, demonstrating that precise adjustment of pressure points is essential for enhancing calibration accuracy.

In the automatic target-setting method, the polynomial regression-based model was shown to provide consistent target values even when samples were replaced, ensuring the reliability of the calibration process. Compared to the conventional manual target-setting method, the automated approach was found to be superior in terms of both efficiency and accuracy

Additionally, since the temperature range used in this study was limited, it is possible that the influence of temperature points appeared to be relatively less significant. If the temperature range were expanded beyond the current test conditions, temperature points could also have a greater impact on the calibration process. This suggests that in real-world environments, where sensors are exposed to a wider range of temperatures, responding to temperature changes could be crucial.

5. Conclusions

We confirmed the impact of increasing the number of pressure and temperature points on the calibration accuracy of pressure sensors. The results showed that the number of pressure points has a greater effect on improving linearity than the number of temperature points, which is likely due to the higher sensitivity of the sensor to pressure changes. Therefore, this demonstrates the importance of increasing the number of pressure points to enhance the accuracy of pressure sensors.

Additionally, we confirmed that the automatic target-setting method using a polynomial regression-based model can provide consistent target values even when samples are replaced. This method improves efficiency and accuracy compared to the manual target-setting approach, proving to be an effective way to increase the reliability of the pressure sensor calibration process.

This study indicates that combining multiple calibration points with an automated target-setting method enhances both the accuracy and efficiency of pressure sensor calibration, making it a promising approach for broader applications in industrial settings where precise measurements are critical.

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Appendixes

Appendix 1: 2 temperature points and 3 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	

70	0	0.007	0.0974	3050	22640
	21.11	10.0	10.0902	6856	
	95.36	45.0	45.0893	20302	

Appendix 2: 2 temperature points and 4 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
70	0	0.007	0.0974	3050	22640
	21.11	10.0	10.0902	6856	
	74.04	35.0	35.0896	16444	
	95.36	45.0	45.0893	20302	

Appendix 3: 3 temperature points and 2 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
40	0	0.007	0.0974	3114	18714
	95.36	10.0	45.0893	21562	
70	0	0.007	0.0974	3050	22640
	95.36	45.0	45.0893	20302	

Appendix 4: 3 temperature points and 3 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
10	0	0.007	0.0974	3184	14184
	21.11	10.0	10.0902	7542	
	95.36	45.0	45.0893	22988	
70	0	0.007	0.0974	3050	22640
	95.36	45.0	45.0893	20302	

Appendix 5: 3 temperature points and 4 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
10	0	0.007	0.0974	3254	14184
	21.11	10.0	10.0902	7542	
	74.16	35.0	35.0896	18544	
	95.36	45.0	45.0893	22988	
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
70	0	0.007	0.0974	3050	22640
	95.36	45.0	45.0893	20302	

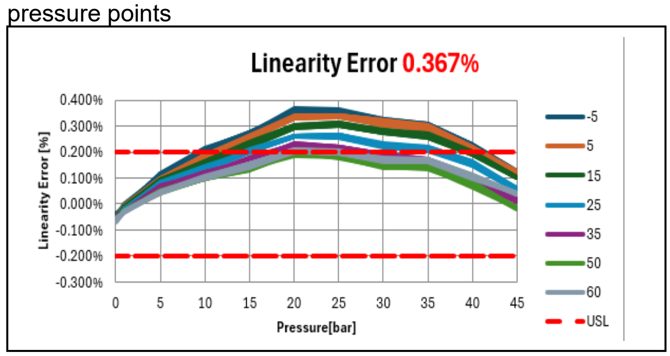
Appendix 6: 4 temperature points and 2 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
10	0	0.007	0.0974	3184	14184
	95.36	45.0	45.0893	22988	
40	0	0.007	0.0974	3114	18714
	95.36	45.0	45.0893	21562	
70	0	0.007	0.0974	3050	22640
	95.36	45.0	45.0893	20302	

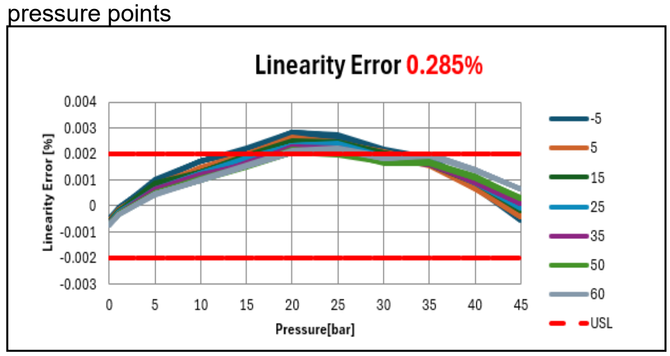
Appendix 7: 4 temperature points and 3 pressure points

Chamber temp.	Press. %	SV[Bar]	PV[bar]	Press. ADC	Temp. ADC
-20	0	0.007	0.0974	3254	9227
	95.36	45.0	45.0893	24626	
10	0	0.007	0.0974	3184	14184
	21.11	10.0	10.0902	7542	
	95.36	45.0	45.0893	22988	
40	0	0.007	0.0974	3114	18714
	95.36	45.0	45.0893	21562	
70	0	0.007	0.0974	3050	22640
	95.36	45.0	45.0893	20302	

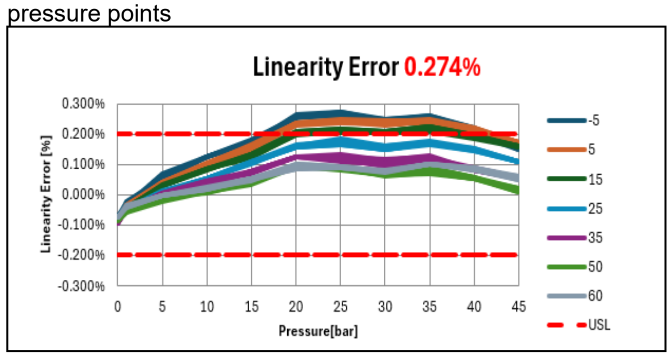
Appendix 8: Linearity error of 2 temperature points and 3 pressure points



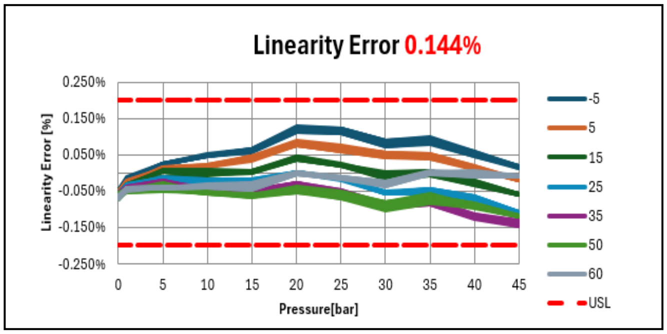
Appendix 9: Linearity error of 2 temperature points and 4 pressure points



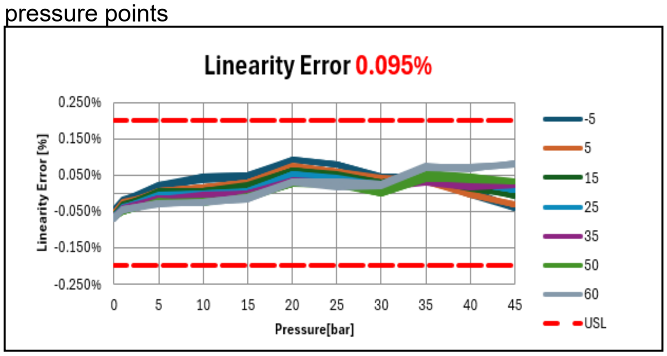
Appendix 10: Linearity error of 3 temperature points and 2 pressure points



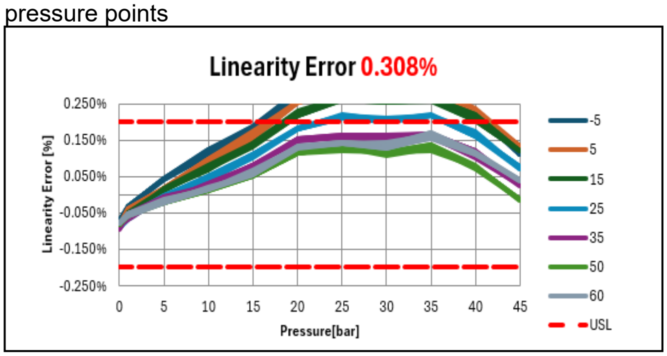
Appendix 11: Linearity error of 3 temperature points and 3 pressure points



Appendix 12: Linearity error of 3 temperature points and 4 pressure points



Appendix 13: Linearity error of 4 temperature points and 2 pressure points



Appendix 14: Linearity error of 4 temperature points and 3 pressure points