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A Practical Technique for Minimizing the Number of Measurements in Sensor Signal Conditioning Calibration

Art Kay, Mikhail Ivanov, Viola Schäffer — High-Performance Linear Products

ABSTRACT

The output of many modern bridge type sensors contains errors that must be eliminated through calibration. One major source of error is variation of sensor span and offset from device to device and their respective drifts with temperature. These drifts can be non-linear. Another source of error is the nonlinearity of the sensor output with applied stimulus. Signal conditioning electronics can also introduce its own errors. The complexity and duration of the calibration process that removes these errors is a major cost factor in the modern sensor production. Multiple measurements have to be made while applying stimulus to the sensor in temperature chambers.

This paper discusses a practical model of sensor behavior vs. input stimulus and temperature based on general pre-characterization data. A sensor calibration method using this model is described where the number of required stimuli and temperature levels is minimized. The measurements are made at the output of a complete module containing the sensor and conditioning electronics thus taking all system errors into account. A programmable signal conditioning amplifier stores the computed calibration data and uses it to eliminate initial errors.

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Contents

1 Introduction

A typical sensor output response for span and offset versus temperature is shown in Figure 1. The goal of the calibration technique described in this paper is to describe a method for amplification and linearization of a low level non-linear sensor signal, and compensation of nonlinear temperature drift of the sensor's span and offset so that the output of the system is a high level signal that does not drift with temperature. The first part of the calibration procedure is to generate a mathematical model for the sensor based on measurements made over temperature and applied stimulus. This model is used to generate table of offset and gain corrections versus temperature. The signal conditioning system will monitor the temperature of the sensor and use the table to cancel the sensor drift. A typical output response of a sensor to applied stimulus is shown in Figure 2. Note that this sensor has a second order nonlinearity error. The sensor signal conditioning system can cancel second order nonlinearity by feeding a portion of the output signal back to the sensor. During calibration the mid-scale nonlinearity is measured. This measurement is used to develop a feedback coefficient that will substantially reduce the nonlinearity error.

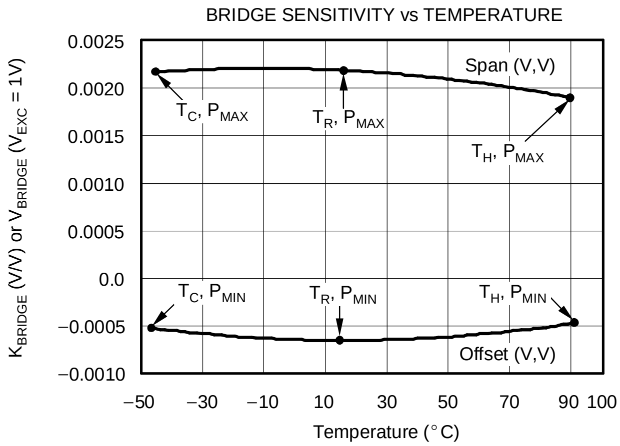

Figure 1. Output Response of a Bridge Sensor vs Temperature

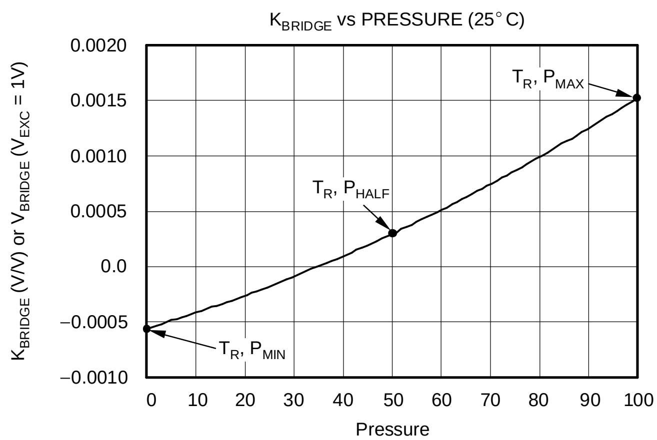

Figure 2. Output Response of a Bridge Sensor vs Stimulus

2 Mathematical Model of a Bridge Sensor

Generally, one can describe each span, offset and nonlinearity parameters as polynomials of *Nth* degree either vs. temperature or vs. input stimulus. In practice it is rarely necessary to compensate higher than 2nd-order errors and span, offset and nonlinearity can be approximated with 2nd-order equations for each. Assuming that sensor nonlinearity is constant with temperature, these equations can be combined together into a mathematical model given by Equation 1. Since bridges are ratiometric sensors, $K_{BRIDGE}(P,T)$ is the sensitivity of the sensor relative to the excitation voltage in V/V. It is a single function of two variables—input stimulus P (such as pressure or flow) and temperature T—and seven coefficients. The coefficients n_0–n_6 are the model parameters.

$$K_{BRIDGE}(P,T) = n_0 + n_1T + n_2T^2 + \left(n_3P + n_4P^2\right)\left(1 + n_5T + n_6T^2\right) \tag{1}$$

Calibrating the sensor requires performing second order curve fits over three measurement points for nonlinearity and temperature drifts of span and offset. This involves making span and offset measurements at three different temperatures. Generating the model for sensor output nonlinearity versus applied stimulus involves making a zero-scale, mid-scale, and full-scale measurement and performing a second order curve fit. Generally one needs to build an *NxNxN* array of measurements to curve-fit the model using three *Nth* degree polynomials [1]. However, since we combined the sensor model into Equation 1 with seven variables, many of the data points are redundant. In our case we can make a total of seven measurements to curve-fit all seven model parameters. Table 1 summarizes the required measurements conditions to solve for the model parameters in Equation 1. Figure 3 illustrates the sensor signal conditioning system. The sensor and temperature calibration measurements are made through this system with K_{LIN} = 0. Making the measurements in this manner has an advantage in that the errors in the signal conditioning system are lumped together with the sensor. Thus, the system errors will also be eliminated during the calibration process.

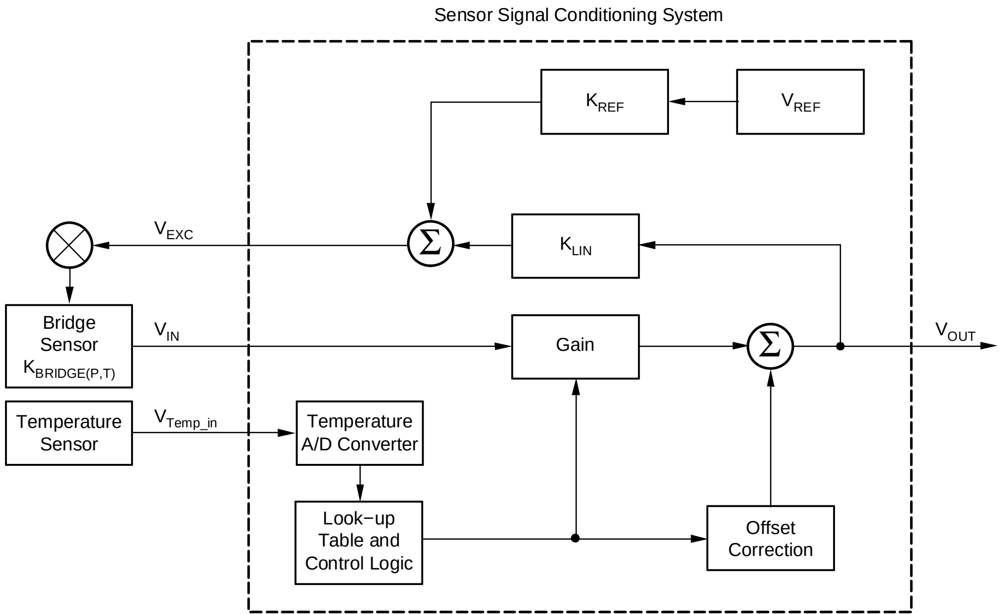

Figure 3. Sensor and Signal Conditioning System

Table 1. Measurement Conditions

TEMPERATURE	PRESSURE	V_{OUT}	$K_{BRIDGE}(P, T)$
T_C	P_{MIN}	V_{OUT1}	$(V_{OUT1} - Offset) / (Gain \times V_{EXC})$
T_C	P_{MAX}	V_{OUT2}	$(V_{OUT2} - Offset) / (Gain \times V_{EXC})$
T_R	P_{MIN}	V_{OUT3}	$(V_{OUT3} - Offset) / (Gain \times V_{EXC})$
T_R	P_{HALF}	V_{OUT4}	$(V_{OUT4} - Offset) / (Gain \times V_{EXC})$
T_R	P_{MAX}	V_{OUT5}	$(V_{OUT5} - Offset) / (Gain \times V_{EXC})$
T_H	P_{MIN}	V_{OUT6}	$(V_{OUT6} - Offset) / (Gain \times V_{EXC})$
T_H	P_{MAX}	V_{OUT7}	$(V_{OUT7} - Offset) / (Gain \times V_{EXC})$

The mathematics behind solving for the model parameters involve solving three matrices. Solving the first matrix involves eliminating the pressure dependent portion of Equation 1 by setting pressure to zero at all three temperatures (Equation 2). In practical applications it may not be possible to attain a zero pressure, and so substituting $P = P - P_{MIN}$ is used in all equations. The second matrix is solved by setting pressure to maximum at all three temperatures using the model parameters from the first matrix (Equation 3). The last matrix is solved by setting the temperature to room for mid-scale and maximum pressure (Equation 4).

Let P = P_{MIN} = 0:

$$K_{BRIDGE}(T) = n_0 + n_1 T + n_2 T^2$$

$$\begin{pmatrix} n_0 \\ n_1 \\ n_2 \end{pmatrix} = \begin{bmatrix} K_{BRIDGE}(P_{MIN,} T_C) \\ K_{BRIDGE}(P_{MIN,} T_R) \\ K_{BRIDGE}(P_{MIN,} T_H) \end{bmatrix} \cdot \begin{pmatrix} 1 & T_C & T_C^{\,2} \\ 1 & T_R & T_R^{\,2} \\ 1 & T_H & T_H^{\,2} \end{pmatrix}^{-1} \tag{2}$$

Let P = P_{MAX}:

$$K_{BRIDGE}(P_{MAX,} T_C) = n_0 + n_1 T + n_2 T^2 + \left(n_3 P_{MAX} + n_4 P_{MAX}^{\,2}\right)\left(1 + n_5 T_C + n_6 T_C^{\,2}\right)$$

$$\begin{pmatrix} 1 \\ n_5 \\ n_5 \end{pmatrix} = \begin{bmatrix} K_{BRIDGE}(P_{MAX,} T_C) - \left(n_0 + n_1 T_C + n_2 T_C^{\,2}\right) \\ K_{BRIDGE}(P_{MAX,} T_R) - \left(n_0 + n_1 T_R + n_2 T_R^{\,2}\right) \\ K_{BRIDGE}(P_{MAX,} T_H) - \left(n_0 + n_1 T_H + n_2 T_H^{\,2}\right) \end{bmatrix} \cdot \begin{pmatrix} 1 & T_C & T_C^{\,2} \\ 1 & T_R & T_R^{\,2} \\ 1 & T_H & T_H^{\,2} \end{pmatrix}^{-1} \cdot \frac{1}{\alpha} \tag{3}$$

Let T = T_R, P = P_{HALF};and let T = T_R, P = P_{MAX}:

$$\begin{pmatrix} n_3 \\ n_4 \end{pmatrix} = \begin{bmatrix} \dfrac{K_{BRIDGE}(P_{HALF,} T_C) - \left(n_0 + n_1 \cdot T_C + n_2 T_C^{\,2}\right)}{\left(1 + n_5 \cdot T_C + n_6 T_C^{\,2}\right)} \\ \dfrac{K_{BRIDGE}(P_{MAX,} T_C) - \left(n_0 + n_1 \cdot T_C + n_2 T_C^{\,2}\right)}{\left(1 + n_5 \cdot T_C + n_6 T_C^{\,2}\right)} \end{bmatrix} \cdot \begin{pmatrix} P_{HALF} & P_{HALF}^{\,2} \\ P_{MAX} & P_{MAX}^{\,2} \end{pmatrix}^{-1} \tag{4}$$

3 Correcting Nonlinearity versus Applied Stimulus Using Feedback

Temperature drift correction involves converting temperature to a digital value and adjusting the system's gain and offset to compensate for the errors. This method is works well because temperature drift is a slow moving function, but correction of linearity errors versus applied stimulus requires a purely analog technique because the excitation can be a fast moving signal. For second order nonlinearities versus applied stimulus it is possible to feed back a portion of the output signal to the sensor to cancel the nonlinearity. The method can be intuitively understood by considering that the response of the sensor conditioning system can be approximated as second order. The exact response of the system is a ratio containing multiples of K_{LIN} in the numerator and denominator (Equation 5). For a linear input the response can be represented as an infinitely long polynomial using a Taylor series expansion. Table 2 illustrates the error in comparing different order Taylor expansions to the exact solution. Note that the error is relatively small for the second order expansion indicating the system response can be approximated as second order. Also note that this example uses K_{LIN} = –0.16 which will correct for a 5% nonlinearity. Smaller K_{LIN} terms would be an even better approximation of a second order function.

$$V_{OUT} = \frac{K_{BRIDGE} \cdot V_{REF} K_{REF}\ \mathrm{Gain} + V_{offset\_correction}}{1 - K_{BRIDGE} \cdot K_{LIN}\ \mathrm{Gain}} \tag{5}$$

Figure 4 illustrates graphically how the correction technique works. The uncorrected sensor has a positive P^2 coefficient (i.e., concave up). By selecting the appropriate sign magnitude of K_{LIN}, the system response is designed to cancel the sensors response (i.e., the system response is concave down). When the sensor is connected to the system, the combined response forms a linear output. This method will typically yield a 20:1 improvement in linearity error.

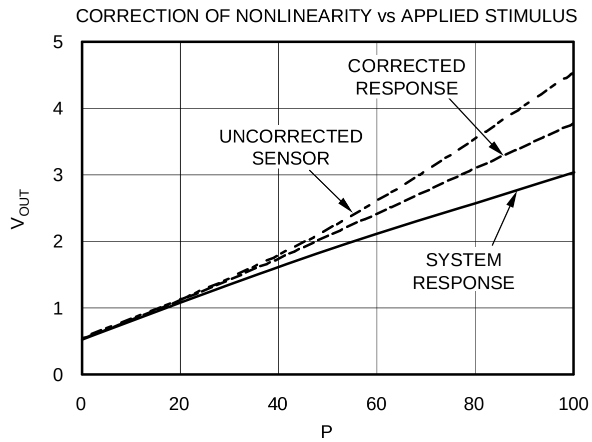

Figure 4. System Nonlinearity Cancels Sensor Nonlinearity

Table 2. Taylor Expansion vs Exact Solution

ITERATION (ORDER OF POLYNOMIAL)	TAYLOR APPROXIMATION ERROR TO EXACT SOLUTION (% OF FULL-SCALE)
1	0.687
2	–0.127
3	0.023
4	–0.004

The equation used to select the value of K_{LIN} required to cancel second order nonlinearity is derived by forcing the closed loop system output response to have zero linearity error at mid-scale. Mid-scale is the point of largest linearity deviation. The nonlinearity is analyzed at room temperature only and assumed to be the same over temperature. For mathematical simplicity, K_{BRIDGE} is replaced with its normalized equivalent K_P (see Equation 6 and Equation 8). B_V is the mid-scale nonlinearity (see Equation 7). Also, the offset correction is combined with $K_{BRIDGE}(0)$ to form V_{OUT_MIN}. Thus, Equation 5 can be rewritten as Equation 9. The constraint $K_P = 1$ at $_{PMAX}$, and the constraint $K_P = 0.5 + B_V$ for an ideal linear output is applied to Equation 9 to yield Equation 10.

$$K_P(P) = \frac{K_{BRIDGE}(P) - K_{BRIDGE}(0)}{FSS} \tag{6}$$

$$B_V = \frac{K_P(50) - \frac{K_P(100) + K_P(0)}{2}}{K_P(100) - K_P(0)} \tag{7}$$

$$K_P = \left[\frac{P + 4(B_V)\,P_{MAX}\left[\left(\frac{P}{P_{MAX}}\right) - \left(\frac{P}{P_{MAX}}\right)^2\right]}{P_{MAX}}\right] \tag{8}$$

$$V_{OUT} = \frac{\left[(FSS \cdot G \cdot K_P V_{REF} K_{REF}) + V_{out\_min}\right]}{\left[1 - (FSS \cdot G \cdot K_P K_{LIN})\right]} \tag{9}$$

$$K_{LIN} = \frac{4 B_V V_{REF} K_{REF}}{\left(V_{OUT\_MAX} - V_{out\_min}\right) - 2B_V\left(V_{OUT\_MAX} + V_{out\_min}\right)} \tag{10}$$

4 Compensating the Sensor versus Temperature Drifts

The mathematical model of the sensor is used to generate a table of offset and gain corrections versus temperature. In a practical system, the length of this table is limited in size. For this example we use 17 points in the table. Between points, a linear interpolation is used to estimate the value of the correction factor. A calibrated signal conditioning system will monitor the temperature of the sensor, compare the temperature to the table and adjust its gain and offset to cancel the drift effects. Figure 5 and Figure 6 illustrate how the sensor span drift is canceled by adjusting gain. Offset drift is corrected in a similar manner. Figure 7 illustrates the interpolation error that is introduced during the linear interpolating between points in the table.

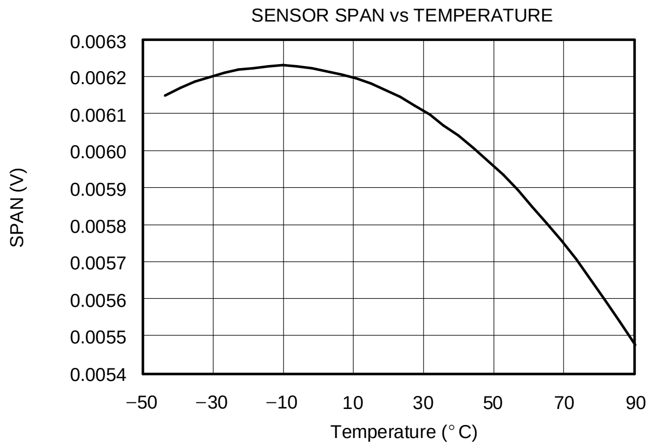

Figure 5. Sensor Span Drift

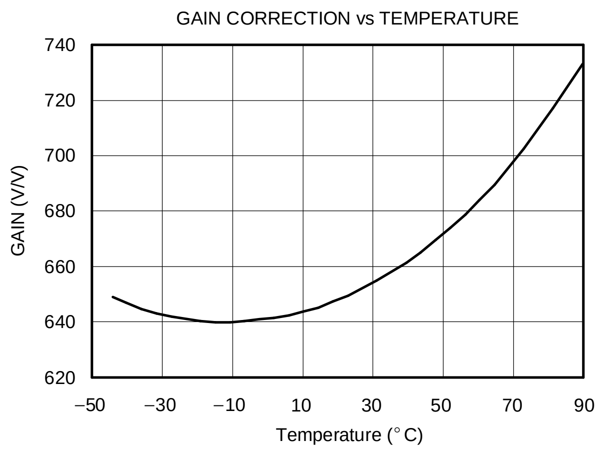

Figure 6. Gain Correction

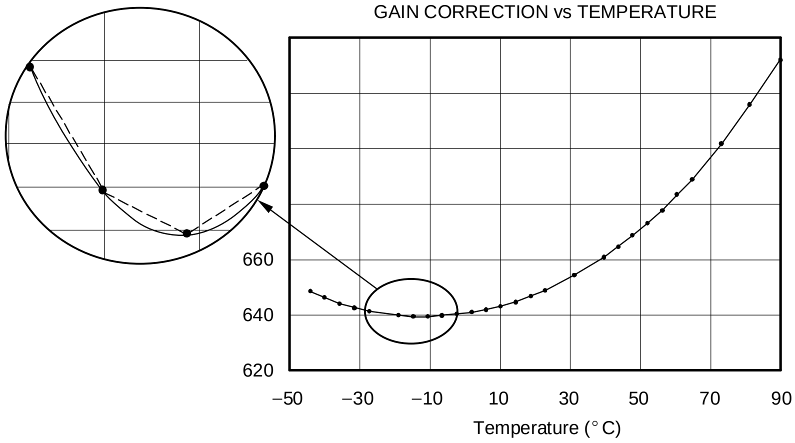

Figure 7. Error Caused by Interpolation

5 Practical Implementation of the Sensor Signal Conditioning System

The Texas Instruments PGA309 integrated circuit chip is an example of a sensor signal conditioning system that follows the basic topology described in this paper. The gain, and offset correction are implemented with 16-bit digital-to-analog converters (DACs). The sensor temperature can be monitored using an external or internal diode and onboard 16-bit delta-sigma converter. Adjustment of the linearity feedback factor (K_{LIN}) is accomplished using a 7-bit DAC. The block diagram for this device is shown in Figure 8. The end result of a calibration using this device is that a sensor with initial deviations up to 50%, nonlinearity errors on the order of 4%, and gain drifts on the order of 20% of span are calibrated to have a total error less than 0.1% [2] [3].

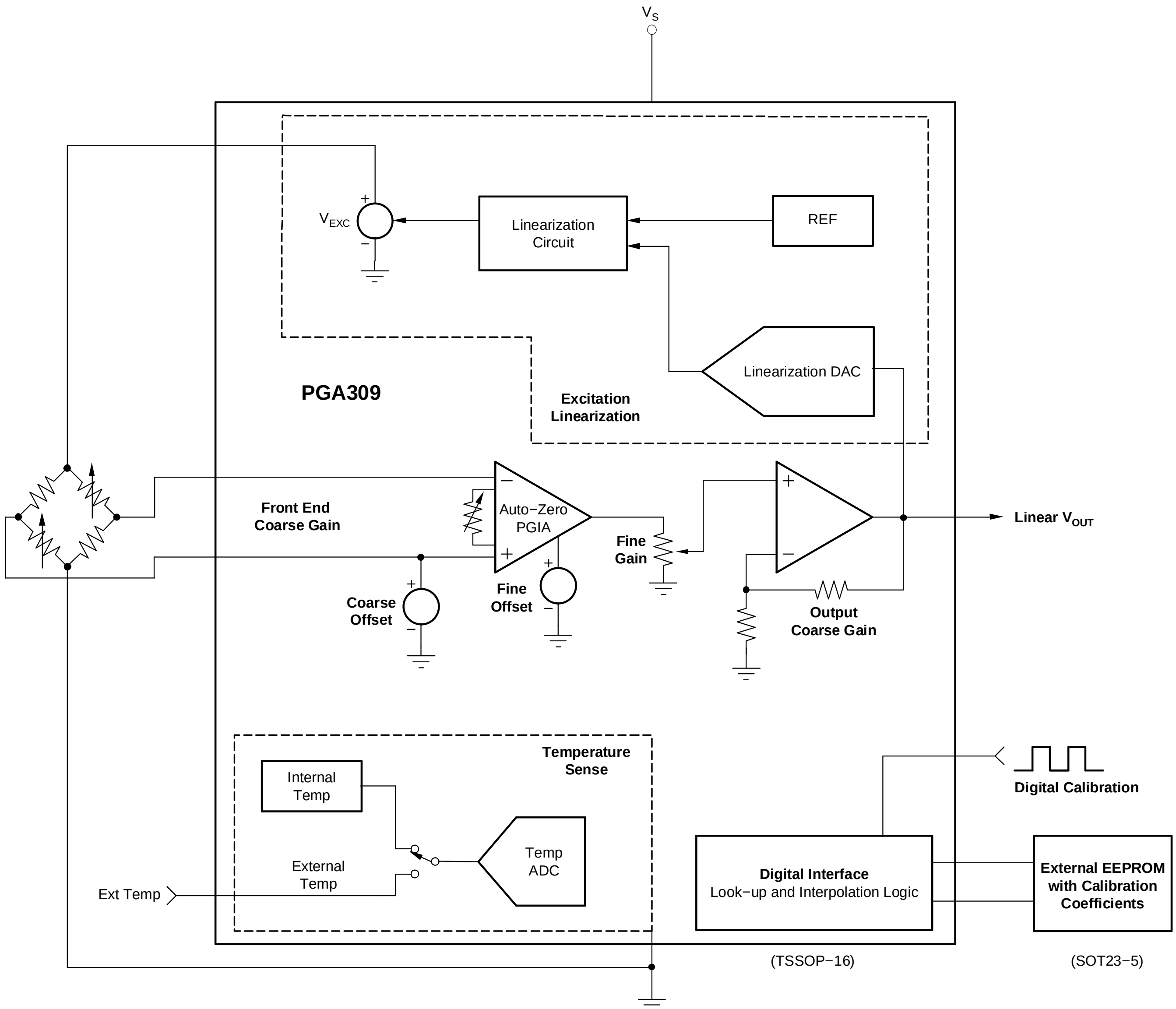

Figure 8. Block Diagram of PGA309 Integrate Sensor Signal Conditioning System

6 References

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