Investigating quantization errors and their influence on capability of MEMS products Case study: Heavy Vehicle TPM (Tyre Pressure Monitoring) Sensor

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Chapter 1

Abstract

The motivation for this thesis has been to clarify the significance of quantization errors in MEMS (Micro Electro-Mechanical System) products and to see how they combine with normal distribution errors. As a case study, an integrated absolute pressure sensor for the automotive market was chosen. Combinations of errors in such sensors are often treated as if they were simple normal distributions and question was if this is sufficiently correct when considering spread in accuracy and when at the end considering final product capability.

For a product to be capable of meeting its performance specification at the highest possible yield level it is important to find the most correct way of calculating capability. Many natural parameters are normal distributed and in practice one often assumes data distributed such way. This has also been the practice for the heavy vehicle TPM (Tyre Pressure Monitoring) sensor from Infineon Technologies SensoNor, the sensor selected herein as a case study. It has quantization in the signal path. However it is assumed that the errors are normal distributed when calculating its capability. This was background for the establishment of this thesis, with the literal quotation to

> To investigate quantization errors and their influence on capability of MEMS products.

The heavy vehicle TPM sensors are calibrated, meaning errors from digitizing during this process also contributes in the error picture and effects capability.

Theoretical calculations, simulations and measurements are performed. Results are analyzed, compared, and discussed in order to conclude and give design considerations for future products.

All together 4 simulation models were established. The last of the models made, the Final Model, was the most flexible one, being able to simulate both the sensor and the calibration process. Different error contributions from LNA gain change, different ADC resolutions, and different coefficient round offs were analyzed and discussed. The sources of errors were considered such way that it came clear how they contributed to spread isolated and in combination with each other.

Especially in focus through out this work was a specific LNA (Low Noise Amplifier) gain reduction for the heavy vehicle TPM sensor. What change in error contributions such a reduction of the signal gain before quantization give, and how it at the end effects the total product capability.

It was concluded that a LNA gain reduction results in larger spread in sensor measurement performance, and that it at the end makes the product less capable. It was also concluded that coefficient round offs, especially round offs for one sensor PROM coefficient ($PZ1_{PROM}$), gave significantly increased error on the pressure output signal when reducing LNA gain. A reduction from LNA gain 16 to LNA gain 10 gave an increase in ($PZ1_{PROM}$) round off error with a factor of 1.6, from 1.37 to 2.19 kPa for the worst situation (at the highest temperatures) for 2.5 sensors simulated.

Based on the ($PZ1_{PROM}$) finding it was recommended to optimize PROM coefficient scalings for future TPM sensor designs.

Chapter 2

Introduction

The project has been carried out as a master thesis in collaboration between the Institute for Microsystem Technology (IMST) at the College of Vestfold (HVE), and the company, Infineon Technologies SensoNor AS.

Tyre Pressure Monitoring Systems (TPMSs) are considered a safety application for cars and trucks in the 21th century. Having an accurate monitoring system for tyre pressure makes it easier keeping tyres from being underinflated. Keeping the tyre pressure inside manufacturer's recommendations is important. There are several aspects with it. Correct tyre pressure is considered a safety, environmental and economical issue, and

- Reduces the risk for fatal injuries on the road (safety asp.)

- Reduces fuel consumption and CO_2 emmision (environmental asp.)

- Increases tyre lifetime (economical asp.)

NHTSA ([1]) states on one of their web sites that approximately 120 motor vehicle fatalities and 8500 injuries can be prevented annually in the United States alone having all passenger vehicles equipped with TPMS. After a series of fatal car accidents related to tyre failures in the late 90's and 2000 a well known *TREAD act.* ([2]) was signed by President Clinton 1st Nov, 2000, claiming for a federal law for a tyre pressure monitoring system. This resulted later in a final rulemaking ([3]), from NTHSA, claiming TPMS mandatory for all vehicles less than 10000 pounds, from model year 2008 at the latest.

The advantages of having installed a TPMS are all important, and the system performance rely in the highest degree on the performance of the tyre pressure sensor. This sets the profession of making tyre pressure sensors in a higher context.

When looking closer at the sensor, it was interesting to consider how to determine its pressure performance and capability. The mean and spread values of the reported pressure from the sensor are calculated, giving the basis for capability measures. Quantized values from ADC (Analog to Digital Converter) conversion and round offs in PROM (Programmable Read Only Memory) coefficients has an inevitable effect increasing spread. They give distinct, non-continuous values, making correct capability calculations more complex than with only normal distribution errors. They also give uncorrelated error contributions, e.g. like ADC and coefficient round off errors, meaning independent of each other. For the purpose of ease and simplicity, and since it perhaps does not have to be done otherwise to be sufficiently accurate, capability calculations for such MEMS devices as the heavy vehicle TPM sensor are often considered in whole as giving a normal error distribution. How this simplification makes a difference for spread and capability conclusions for sensors produced is interesting. Is there as significant difference or not.

Different error contributions in the heavy vehicle tyre pressure sensor were especially considered when the LNA gain, Gp, was reduced. This sensors is based on a lower pressure range sensor and the range extension called for a gain reduction in the ADC to prevent it from overflowing at the highest pressures. The gain of the LNA amplifier was reduced from 16 to 10. This topic is very specific, and this thesis deals with it as one of the main tasks of investigation. To see how the quantization errors contribute, isolate and together with coefficient truncating error.

Chapter 3

Background Information

3.1 High Capability Requirements for Automotive applications

In the automotive business it is well established to require low ppm (parts per million) failure rates. Sensor product specifications are expected to reflect as high as 6 sigma (σ) values for product performance. The specification limits are set during product design period already and by looking at extensive measurement results from *product characterization*.

As part of releasing a product for high volume production, product performance is further verified in *product qualification*. A certain number of sensors, typically 77 parts from 3 different lots, are taken out for distinct extensive tests in a *qualification program*. The AEC-Q100 standard, provided by the acknowledged Automotive Electronics Council (AEC), [4], defines how to run such a qualification program for automotive sensors.

The reason for using probability statistics for specifying product performance in automotive business segment is to focus and rely on process control and thereby avoid 100% testing of all components at all corners of temperature and pressure. When having a high number of sensors produced, one can still easily sample a sufficiently high representative number of sensors among the total population to verify performance. Sampling somewhere between 0.1 and 1 % of the total amount of sensors produced is normal. These production verification tests confirm product capability contineously through out production. If the results show non-capability, alerts are raised and the failing sensors are handled in failure analysis programs.

3.2 Heavy Vehicle TPM Sensor

Infineon Technologies SensoNor has several cutting edge Si based MEMS sensors available, as various pressure sensors and inertia sensors, all designed for the automotive market. The company has had pressure sensors as its core business since established in 1985. The heavy vehicle TPM sensor belongs to the $4th$ generation TPM sensors. All of today's sensors digitize the sensor die pressure signal for flexibility and control reasons.

The pressure monitoring sensor exist of two parts; The pressure sensor die and the ASIC (Application Specific Integrated Circuit). The ASIC is where the digitizing takes place. The sensor die and ASIC die are interconnected by wire bonding and encapsulated in a transfer moulded plastic package. The ASIC outputs fully compensated sensor die data. *Fig. 3.1* shows schematically the heavy vehicle TPM sensor package and internals.

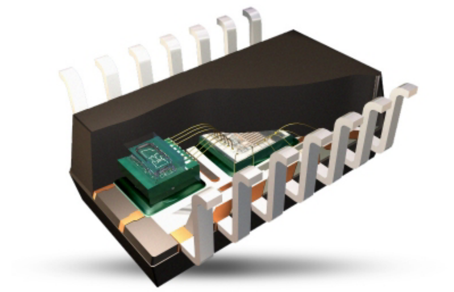


Figure 3.1: Schematics of heavy vehicle TPM sensor. ASIC and sensor die in package.

Packaging is done by plastic transfer molding. *Fig. 3.2* shows schematically how the heavy vehicle TPM sensor measures and compensates pressure. T_{in} is applied temperature, v_p is pressure die output signal, G_p is LNA gain, G_{adc} is ADC gain, P_{adc} is ADC output, P_{res} is pressure resolution, T_{comp} is compensated temperature, and $PS0_{PROM}$, $PS1_{PROM}$, $PS2_{PROM}$, $PZ0_{PROM}$, $PZ1_{PROM}$ and $PZ2_{PROM}$ are digitized and scaled coefficient, PROM coefficients. P_{in}, P_{raw}, and P_{comp} are described in *Tab. 3.2*.

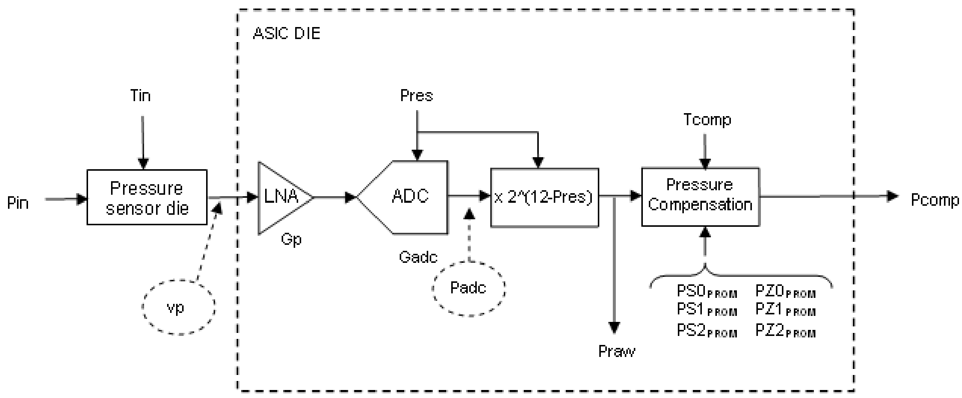


Figure 3.2: Heavy vehicle TPM sensor pressure measurement and compensation schematics.

3.2.1 Pressure Calibration

Sensor calibration is a trade-off between time/cost and test coverage in high volume production. For the heavy vehicle TPM sensor there are used four measurement points for calibration. Several ADC measurements are done at each measurement point in order to average to more precise values before calculating PROM coefficients. Tab. 3.1 lists the calibration points.

All six pressure sensor die parameters (ps0, ps1, ps2, pz0, pz1 and pz2) are determined, digitized, scaled as PROM coefficients, and programmed. When this is done, the sensors are said to be calibrated.

Table 3.1: Pressure calibration points for heavy vehicle TPM sensor.

Measurement point	Temperature / Pressure
LT - Low Temperature	-20 °C / 100 kPa
HT - High Temperature	70 °C / 100 kPa
HP - High Pressure	25 °C / 657.5 kPa
AP - Atmospheric Pressure	25 °C / 100 kPa

3.2.2 Pressure Compensation

Pressure sensor compensation is the corrections of the digitized pressure sensor die result forwarded from the ADC, over the full pressure and temperature range.

The PROM coefficients have the same name as the sensor die parameters for consistency, just in capital letters and with the extension *PROM*, meaning they become $PS0_{PROM}$, $PS1_{PROM}$, $PS2_{PROM}$, $PZ0_{PROM}$, $PZ1_{PROM}$, and $PZ2_{PROM}$. They have limited resolutions, from 8 to 16 bits, signed or unsigned, and together with the scaling and mathematics used, they naturally introduce some quantization errors. The significance of the error vary with Gp, ADC resolution, temperature and pressure.

Some pressure definitions of interest, related to the heavy vehicle TPM sensor and its pressure measurements are found in *Tab. 3.2*.

Table 3.2: Heavy vehicle TPM sensor measurement parameters, their descriptions, and their units.

Parameter	Description	Unit
P_{in}	Applied pressure	kPa
P_{raw}	ADC raw pressure data output	LSB
P_{comp}	Compensated pressure	LSB
P_{out}	Calculated pressure	kPa

3.2.3 Pressure Characterization

Characterization runs are performed to verify the capability of calibration. For the heavy vehicle TPM sensor such a run is typically a *5x5x3 run*, meaning a run over 5 pressures, 5 temperatures and 3 supply voltages, giving 25 verification points at each supply voltage (*Tab. 3.3*).

Table 3.3: Example of heavy vehicle TPM sensor pressure characterization run.

Parameter	Set point	Unit
5 pressures	100, 657.5, 1000, 1250, 1500	kPa
5 temperatures	-40, -20, 25, 70, 125	°C
3 supply voltages	2.1, 3.0, 3.6	V

3.3 Model of The Heavy Vehicle TPM Sensor

The sensor model for the pressure sensor (not to be mixed with the *sensor simulation model*) is central for establishing the simulation models correctly. Each sensor parameter describing the pressure sensor die performance is listed in *Tab. 3.4*([9]). The typical, min and max parameter values are interesting for the modeling as this tells the variations to be expected.

Some, however not all, pressure sensor parameters are considered to have variations in the later described simulations. The considerations are based on sensor die characterization results, whereas some parameters show very little variation. These parameters showing little variation was set constant at typical values for the simulations. (The same is done when calibrating sensors in production).

Six parameters are describing the sensor die performance of the heavy vehicle TPM sensor in terms of its pressure sensitivity and zero point over the full supply voltage, pressure, and temperature range. These coefficients are:

Table 3.4: Heavy vehicle TPM sensor die parameters.

Sensor parameter	Description	Unit
ps0	Sensitivity	µV/VkPa
ps1	1st order temperature dependency of sensitivity	1/°C
ps2	2nd order temperature dependency of sensitivity	$1/°C^2$
pz0	Zero point	µV/V
pz1	1st order temperature dependency of zero point	µV/V °C
pz2	2nd order temperature dependency of zero point	$\mu V/V\ °C^2$

To be able to simulate the pressure sensor it is important to know the mathematics describing its behaviour from input to output, i.e. to know its transfer function.

The sensor die output signal is defined by([10]):

$$v_p = \frac{ps0 \cdot P_{in} + pz0 + pz1 \cdot (T_{in} - 25) + pz2 \cdot (T_{in} - 25)^2}{1 + ps1 \cdot (T_{in} - 25) + ps2 \cdot (T_{in} - 25)^2} \tag{3.1}$$

Where:

v_p is the sensor die output signal in µV/V

The ADC output after pressure conversion is given by ([10]):

$$P_{adc} = v_p \cdot G_p \cdot G_{adc} \tag{3.2}$$

Where:

G_{adc} is the ADC gain in LSB/(V/V), given by design as ([10]):

$$G_{adc} = 2^{res}/(2 \cdot 0.88) \tag{3.3}$$

The ADC output signal is a scaled to 12 bits and becomes the raw data signal ([10]):

$$P_{raw} = P_{adc} \cdot 2^{12-res} \tag{3.4}$$

Fig. 3.2 gives a graphical presentation of the resolution dependent scaling.

Combining *Eq. 3.2*, *Eq. 3.3*, and *Eq. 3.4* gives the expression for P_{raw} which is resolution independent, but linearly dependent of the LNA gain, G_p:

$$\begin{aligned} P_{raw} &= v_p \cdot G_p \cdot 2^{(12-res+res)}/(2 \cdot 0,88) \\ &= v_p \cdot G_p \cdot 2^{12}/(1,76) \\ &= v_p \cdot G_p \cdot G12 \end{aligned} \tag{3.5}$$

The six sensor die parameters are digitized to be able to compensate the sensor. After digitizing the parameters, the expression for raw pressure data in LSB's is given as ([10]):

$$P_{raw} = \frac{PS0 \cdot P_{in} + PZ0 + PZ1 \cdot (T_{in} - 25) + PZ2 \cdot (T_{in} - 25)^2}{1 + PS1 \cdot (T_{in} - 25) + PS2 \cdot (T_{in} - 25)^2} \quad (3.6)$$

Where:

PS0, PS1, PS2, PZ0, PZ1 and PZ2 are digitized sensor parameters

After leaving the scaling block of the ADC the amplified and digitized sensor die signal is further handled by the pressure compensation routine. Sensor library routines are taking the digitized sensor parameters as input and compensate the sensor over the full temperature and pressure range.

Ideally the relation between compensated pressure, P_{comp}, input pressure, P_{in}, and resolution, Rp, for the heavy vehicle TPM sensor, is given by ([10]):

$$P_{comp} = P_{in} \cdot 2^6 / R_p \Leftrightarrow P_{in} = P_{comp} \cdot R_p / 2^6 \quad (3.7)$$

By substituting *Eq. 3.7* into *Eq. 3.6* and re-arranging, compensated pressure is given with the digitized coefficients as ([10]):

$$P_{comp} = \frac{2^6}{PSO \cdot R_p} \cdot \left[P_{raw} \cdot \left(1 + PS1 \cdot \Delta T + PS2 \cdot \Delta T^2\right) - \left(PZ0 + PZ1 \cdot \Delta T + PZ2 \cdot \Delta T^2\right)\right] \quad (3.8)$$

Where:

(T_{in}-25) equalt to ΔT

The compensation routine of the heavy vehicle TPM sensor does not handle the digitized coefficients directly. It handles the *PROM coefficients*, stored in the device specific memory. Before the coefficients are stored, scalings are done according to *Tab. 3.5*([10]), for each of the coefficients according to calibration results. This is done to obtain higher digital integer values giving only smaller round off errors in pressure compensation.

Table 3.5: Relations between sensor die parameters, digitized sensor die parameters, and PROM coefficients.

Sensor parameter	Digitized	PROM coefficient
ps0	PS0=ps0$\cdot$ $G_p\cdot$ G_{12}	$PS0_{PROM}$=2^{12}/(PS0$\cdot$ R_p)
ps1	PS1=ps1	$PS1_{PROM}$=PS1$\cdot 2^{16}$
ps2	PS2=ps2	$PS2_{PROM}$=PS2$\cdot 2^{23}$
pz0	PZ0=pz0$\cdot$ $G_p\cdot$ G_{12}	$PZ0_{PROM}$=PZ0$\cdot 2^{2}$
pz1	PZ1=pz1$\cdot$ $G_p\cdot$ G_{12}	$PZ1_{PROM}$=PZ1$\cdot 2^{5}$
pz2	PZ2=pz2$\cdot$ $G_p\cdot$ G_{12}	$PZ2_{PROM}$=PZ2$\cdot 2^{13}$

After taking the relations given in *Tab. 3.5* into account, the expression for the compensated pressure data, P_{comp}, expressed with PROM coefficients, arrives at ([10]):

$$\begin{aligned} P_{comp} =& PSO_{PROM} \cdot 2^{-6} \cdot P_{raw} \cdot \left(1 + PS1_{PROM} \cdot 2^{-16} \cdot \Delta T + PS2_{PROM} \cdot 2^{-23} \cdot \Delta T^2\right) - \\ & PSO_{PROM} \cdot 2^{-6} \cdot \left(PZ0_{PROM} \cdot 2^{-2} + PZ1_{PROM} \cdot 2^{-5} \cdot \Delta T + PZ2_{PROM} \cdot 2^{-13} \cdot \Delta T^2\right) \end{aligned} \quad (3.9)$$

To finally calculate the measured pressure from the compensated, P_{comp}, which is gotten from the heavy vehicle TPM sensor when performing pressure measurements *Eq. 3.10* is used:

$$P_{out} = P_{comp} \cdot 2^{-6} \cdot R_p \tag{3.10}$$

Chapter 4

Theory

To build up basic understanding for the case some theory for capability, normal distribution error, and quantized errors is needed.

4.1 Capability

As indicated in the start of *Chapt. 2*, the confidence level of spec limits depends on the number of σ values reflected. The higher the σ value reflected, the higher the confidence level, and thus the higher the probability that the sensor perform inside spec. *Fig. 4.1* ([5]) shows the probability, P, for a data sample (as e.g. sensor pressure measurement) performing inside a certain number of σs provided that the data has a normal distribution. The figure show also what is referred to as the confidence level. On the x-axis $\pm$ 1 σ accounts for 68.3% of all values, while $\pm$ 2 σs and $\pm$ 3 σs account for 95.4 and 99.7 % respectively. Already at 3 σ level, only $\approx$ 0.2 % of the samples (or just 0.1% on each side on the distribution) are not already accounted for. The probability, P, for each sample value is between 0 and 1. The integral of the complete curve from σ=-∞ to σ=+∞ equals 1, thus covering all possible sample values. The highest probability is at the mean value, μ, of the distribution. The percentages on the figure tell the shares of samples falling within $\pm$1, $\pm$2 and $\pm$3 σs. *Tab. 4.1*, [6], shows extensively what are the confidence also for higher σ levels (up to 6 σ). As one can see, operating with 6 σ levels for process and spec limits, gives a high degree of confidence that the product performs within limits. When a process is capable with 6σ limits it is likely that all except $\approx$ 2,0 ppb (parts per billion) are accounted for.

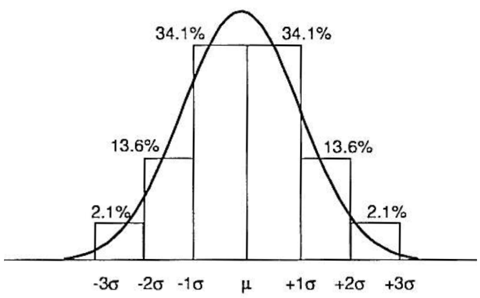


Figure 4.1: Normal distribution. With σs, probability, P, and confidence levels.

Table 4.1: 1 to 6 σ confidence levels for normal distributions.

σ level	Confidence [%]
1	68.2689492
2	95.4499736
3	99.7300020
4	99.9936668
5	99.9999427
6	99.9999998

4.2 Process Capability Calculations

Generally, the definition of process capability is the ability to perform an action. The action in this respect is the heavy vehicle TPM sensor's ability to perform pressure measurements within spec limits. Statistical calculations for product capability are performed by usage of equations for C_p and C_{pk} ([5]). C_p or C_{pk} values equal to 1.0 means the process is marginally capable. Values > 1.0 means its capable. Values < 1.0 means its not capable. All related to 3 σ process capability. To have 6 σ process capability one must require C_p or C_{pk} equal to 2.0 to have marginal capability.

$$C_p = (USL - LSL)/6\sigma \tag{4.1}$$

Where:

Cp estimates the maximum C_{pk} value, the capability if the process could be centered.

$$C_{pk,LSL} = (\mu - LSL)/3\sigma \tag{4.2}$$

Where:

$C_{pk,LSL}$ estimates capability versus the lower spec limit.

$$C_{pk,USL} = (USL - \mu)/3\sigma \tag{4.3}$$

Where:

$C_{pk,USL}$ estimates capability versus the higher spec limit.

When considering process capability either *Eq. 4.2* or *Eq. 4.3* is used. C_{pk} is the smallest of the two:

$$C_{pk} = min(C_{pk,USL}, C_{pk,LSL}) \tag{4.4}$$

4.3 Standard Deviation for Normal Distribution

The standard deviation, normal described by the lower case sigma, σ, is the square root of the variance. The variance is the average of the squared differences from the mean value, μ. When not every member of a population is sampled it is common to divide the squared differences by N-1 instead of N. The explanation for why is complex. Thus the σ expression becomes ([5],[6]):

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{4.5}$$

Where ([5],[6]):

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4.6}$$

4.4 Formulas of Interest for Normal Distribution and Digitized Errors

Formulas herein are later verified in Chapt. 6, Simulations.

4.4.1 Combining Non-Correlated Normal Distribution Errors and Quantized Errors

When analog signals are digitized, as in the sensor ASIC ADCs for calibration and compensation purposes, there will always be round offs or quantizations. The errors introduced in this process are considered *quantization errors*. When there are several independent sources of quantization errors, as well as sources of normal distribution errors, the standard deviation after combination can be determined by taking the square root of the sums of squared contributions. The relation is verified in the simulation part, in *Chapt. 8.1*, and in the measurement part, in *Chapt. 8.2*.

$$\sigma = \sqrt{\sigma_1^2 + \sigma_2^2 + ... + \sigma_n^2} \tag{4.7}$$

4.4.2 Relation between standard deviation and quantization

The quantization error of the ADC is due to it's finite resolution, unavoidable for single measurements. It is resolution dependent in such way that it decreases with increased resolution, and it is always in the range of 0 to 0,5 times the quantization step, again for a single measurement. For rms value of quantization error e, quantization step, Δ, and standard deviation of a quantization error, σ there are relations as given in *Eq. 4.8([7])* and *Eq. 4.9([8])*.

$$e_{rms} = \Delta/\sqrt{12} \tag{4.8}$$

Where:

Δ is the quantization equal to 1 LSB
e_{rms} is the root mean square of the quantization error

$$\sigma e_{rms} = \Delta/\sqrt{12} \tag{4.9}$$

Where:

σ e_{rms} is the standard deviation of the quantization error

Chapter 5

Methods

This chapter describes the work done in form of simulations, measurements and calculations.

5.1 Scope of Work

The work done was determined by the tasks to be solved. The tasks were:

1. To clarify the effect of ADC quantization in terms of product capability. To see how quantized errors combine with normal distribution errors (This raised the need for simulations and calculations)

2. To overall clarify the effects of quantization errors in the heavy vehicle TPM sensor and how this effects product capability. This was more of a general consideration with the aim of identifying separate sources of errors, rank them, and to consider them separately and in combination. (This raised the need for simulations and calculations)

3. To especially look at a case were Gp was reduced from 16 to 10. To determine how this reduction effects the measurement spread, and how it at the end effected the product capability. (This raised the need for simulations, measurements and calculations)

Out from what is listed above, simulation models were made to:

- Simulate the contribution of ADC quantization errors of top of normal distribution errors. A relevant question was: Is it necessary to use the dedicated formulas for combining quantization errors and normal distribution errors calculated from (*Eq. 4.7*), or is it sufficiently correct to use the formulas for normal distributions calculated from (*Eq. 4.5*) when calculating spread of ADC output?

- Simulate the pressure sensor, all the way from variations in sensor die parameters to ADC conversion and pressure compensation, including a Random Normal Distribution Generator (the same generator as used to simulate the ADC quantization)

- Simulate the calibration and characterization process, including a Random Normal Distribution Generator (the same generator as used to simulate the ADC quantization)

- Simulate the pressure sensor in the calibration process, making a final, flexible model were the parameters effecting quantization errors can be adjusted upon user's wish. These adjustments include Gp adjustments (selectable 10 or 16), ADC resolution adjustments (10, 11, or 12 bit + ideal ADC behaviour as a selection), and coefficient round off adjustments (real or ideal for each coefficients)

The Monte-Carlo method were used for the simulations. This method is identified by

1. Defining a domain of possible inputs (determined herein by sensor die parameters)

2. Generate inputs randomly from the domain (work of random normal distribution generator)

3. Aggregate the results of the individual computations into the final results (E.g. the aggregation and further handling of the 2500 simulated ADC results)

Measurements were done for the specific LNA gain reduction in order to:

- Confirm the simulation results for Gp=16 and Gp=10 simulations. The spread in sensor measurement was expected to be inversely dependent of the LNA gain. This raised the need to complete identical measurement runs, except for the difference in LNA gain, on a selected number of parts

NOTE: Quantization errors in terms of round off or truncation errors deeper inside library routines for pressure compensation are outside the scope of work and was thus not considered herein.

The methods for simulation and measurements are further described in *Chapt. 6* and *Chapt. 7*.

Chapter 6

Simulations

Several simulation models had to come in place, and Excel was chosen as simulation tool. It was in focus to make a flexible simulation model at the end, a model that showed different error contributions isolated and in combination with each other - the herein called *Final simulation model.*

All together it was made 3 (4) models. All of them made usage of a random normal distribution generator, which not are listed herein as a separate model. The model named the Final model basically consisted of other models implemented in one larger, flexible model:

- ADC model
- Sensor model
- Process model
- (Final model)

6.1 ADC Model

The heavy vehicle TPM sensor ADC has a sigma-delta ($\Sigma\Delta$) converter, with a 2 MHz crystal oscillator as clock source, and a selectable resolution (5-12 bit).

The *ADC model* simulates the behaviour of the ADC, and is capable of combining normal distribution errors with quantized errors. The error contribution from the ADC quantization is expected to be significant, and highly dependent of the resolution. Higher resolution give less quantization error, naturally.

The model handles all resolutions (5-12). However, quantization, Δ, in the model was not limited to what is obtainable by having small resolutions. Quantizations can be adjusted directly, to much courser steps than obtained by setting low resolutions like 5 and 6 bit.

The purposes of the model was to:

- To verify the theory that tells there is an increased spread with increased quantization

- To verify if there are significant differences between the conventional method for calculating spread, using the formula as given in *Eq. 4.5*, and the method that summarizes the squared contributions before taking the square root of it all, as described in Eq. 4.7

Fig. 6.1 shows schematics for the ADC simulation model. As indicated, it is possible to change either resolution or quantization of the input signal.

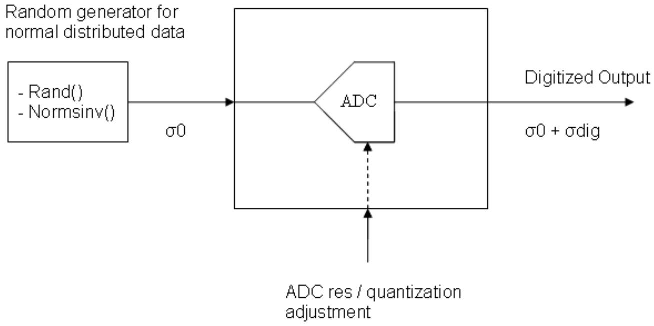


Figure 6.1: Heavy vehicle TPM sensor ADC simulation model.

A Random Normal Distribution Generator, an *ADC input signal generator*, was needed to simulate input signals for the ADC model. Combined functions in Excel were used to simulate sensor die output signals with normal distribution behaviour and make the Random Normal Distribution Generator. The output of RAND() function was as used as input to NORMSINV() function, giving a normal distribution to the ADC model input. A high number of simulated sensor die values ensured a representative amount of normal distribution data to be handled by the ADC simulator. Used number is further discussed in *Chapt. 9.1.*

A customized function is taking the random generated signal, X, and resolution, res, as input parameters to simulating the actual AD conversion. The input signal in the model is normalized with a mean value, $\mu = 0$, and a standard deviation, σ=1. The Excel function STDAV() is used for verification of the generated series of sensor signals.

Quantizations in the ADC are obtained inside the customized function by usage of the ROUND() function. *Eq. 6.1* shows the customized function. Smaller resolutions result in larger quantization errors, and vica versa.

$$ADCCALC_{NORM} = \frac{ROUND(X \cdot (2^{res} - 1), 0)}{(2^{res} - 1)} \tag{6.1}$$

Where the relation between quantization and resolution is given by:

$$\Delta = 1/(2^{res} - 1) \tag{6.2}$$

Substituting *Eq. 6.2* into *Eq. 6.1* replaces resolution with the quantization, making it possible to give quantization, Δ, instead of resolution as input parameter.

$$ADCCALC_{NORM} = \frac{ROUND(X \cdot (2^{\frac{ln(1/\Delta+1)}{ln2}} - 1), 0)}{2^{\frac{ln(1/\Delta+1)}{ln2}} - 1} \tag{6.3}$$

6.2 Sensor Model

The *Sensor* model simulates the behaviour of the heavy vehicle TPM sensor. Input variables are T_{in}, P_{in}, all the six sensor parameters, LNA gain and ADC resolution. Outputs variables are raw data pressure, P_{raw}, and compensated pressure, P_{comp}.

There are several ways of considering sensor die parameter variations for the sensor simulations. They can be considered completely independent of each other, or not. As three coefficients, $PS1_{PROM}$, $PS2_{PROM}$, and $PZ2_{PROM}$ have low variation these were set to constant values, 0,0021/°C, 0/°C^2, and 0 μV/V respectively.

The Random Normal Distribution Generator was used to generate variations of the three other sensor die coefficients. E.g. for generating ps0 values it was done the following way

$$ps0 = 32 + \frac{NORMSINV(RAND())}{6} * 5 \qquad (6.4)$$

Where:

32 is the typical value of pressure sensor die sensitivity.
NORMSINV() and RAND() is the random generator generating the normal ditribution.
The number 6 in the denominator is to make 6 sigma limits for ps0 according to max and min values in the sensor die specification.
The factor 5 is the absolute distance from typ to min and from typ to max values in sensor die specification.

The input pressures and temperature for the sensor simulations were according to *Tab. 6.1*. 3 pressures and 5 temperatures were chosen. All together 15 measurements points, covering the corners of the heavy vehicle TPM sensor product specification, covering also the points where ADC quantization and coefficient round off effects are most significant.

P_{in} [kPa]	T_{in}	P_{in} [kPa]	T_{in}	P_{in} [kPa]	T_{in}
100	-20	657,5	-20	1600	-20
100	0	657,5	0	1600	0
100	25	657,5	25	1600	25
100	70	657,5	70	1600	70
100	125	657,5	125	1600	125

Table 6.1: 3x5 measurements points for sensor simulations.

LAN gain, Gp, was selectable between 25.6, 16 and 10 in the start. Later this was reduced to 16 and 10, to simplify the model, and to be according to the most interesting case dealing with LNA gain change from 16 to 10.

ADC resolution were made selectable. The quantization of the ADC could first of all be REAL or IDEAL, meaning the sensor could be simulated without any ADC quantization error when set to IDEAL. When selected as REAL, the ADCres was selectable between 12, 11 and 10 bits as those are the most interesting ones. Lower resolutions are rarely used (even in TPMS applications were conversion times and current consumptions are crucial).

Round off for coefficients were made selectable, meaning the PROM coefficients could be REAL or IDEAL. When IDEAL they gave no error contribution, and when REAL they resulted in spread in the compensated pressure.

Tab. 6.2 summarizes the selectable parameters for the sensor simulation model in addition to P_{in} and T_{in}.
2 different LNA gains (when not including 25.6), 4 different options for ADCres, and 8 different options for coefficients when considering none, one-by-one and all together, gave totally 3x2x4x8 = 192 plots covering all these combinations. The first factor of 3 comes

LAN gain	ADCres	Coeff Round off
(25.6)	OFF (Ideal)	OFF (Ideal)
16	ON (12 bit)	ON
10	ON (11 bit)	
	ON (10 bit)	

Table 6.2: Adjustable parameters for sensor simulations.

were for making Perr vs T plots for P_{calc} for all three pressures (100, 657.5 and 1600 kPa). However not all of these combinations would be interesting, and thus not even all of them are listen in the appendix (*Sect. A.2.3*).

For each simulation performed there were calculated the measured pressure, P_{out}, from P_{comp} according to *3.2*. Results are found in *Chapt. 8.1*.

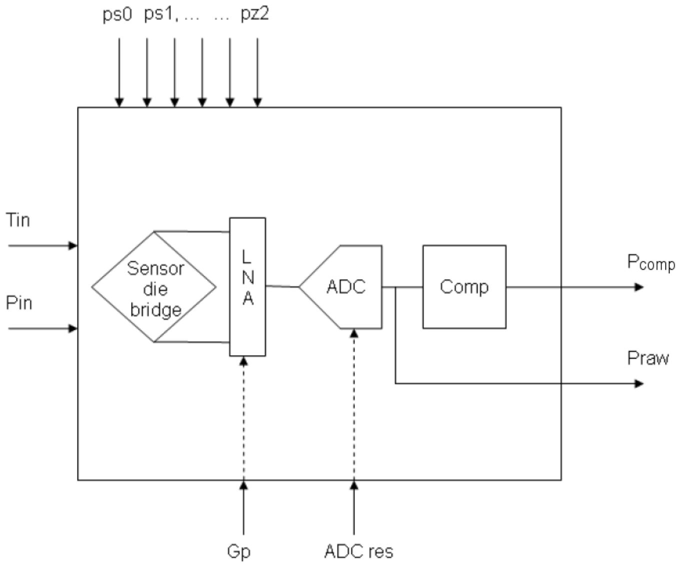


Figure 6.2: Sensor simulation model.

6.3 Process Model

The *Process* model simulates data collection, sensor calibration and characterization as performed in production. The calculated PROM values found here are separated from the values found in the sensor model by calling them CALC PROM values instead of just PROM value or PROM coefficients. First step of the process model was to collect raw pressure data in a data collection step.

Second step was to calculate the three CALC PROMs to be found, $PSO_{CALCPROM}$, $PZ0_{CALCPROM}$ and $PZ1_{CALCPROM}$. $PS1_{CALCPROM}$, $PS2_{CALCPROM}$ and $PZ2_{CALCPROM}$ were set to typical values since of the low variation.

Last step of process model was to perform a characterization to confirm measurement capability.

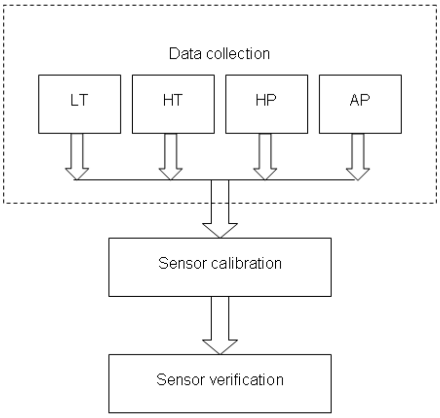


Figure 6.3: Process simulation model.

6.4 Final Model

The aim of the *Final simulation model* is to make the different error sources of the heavy vehicle TPM sensor visible isolated and in combination with each other in a way that visualize the effects as well as puts the results as figures and in table form. The final simulation model is built by assembling the building blocks already established when making the ADC, sensor and process models. Especially by assembling the two latter ones - since the sensor model is built to already include the ADC model.

Especially one thing is in focus for the final simulation model; the LNA gain. It had earlier been seen reduced pressure capability when going from Gp=16 to Gp=10, and thus simulations for Gp=16 and Gp=10 is central. These simulation results, which are found in *Chapt. 8.1*, are also compared to measurement results for verifying theory with measurements.

Inputs to the model are based on the sensor die parameters found in internal documentation. Since three of the parameters are found to have very small variation from die to die and from lot to lot, these were kept constant at typical values during simulations. This is also done in production, meaning it makes the simulations as realistic as possible. This supports to have the best control of the simulation, and give the best fundament for comparison. A listing of individually determined and typically set PROM coefficients are found in *Tab. 6.3*

A high number of sensors, 2500, can be simulated simultaneously in the model. To model more sensors several successive runs can be performed. The randomized sensor signals are generated from functions in Excel, giving fairly good and uniform normal distributions.

Table 6.3: Heavy vehicle TPM sensor coefficient calculations. Individual and typical PROM values.

PROM coefficient	Programmed as
$PS0_{PROM}$	Individual value
$PS1_{PROM}$	Typical value
$PS2_{PROM}$	Typical value
$PZ0_{PROM}$	Individual value
$PZ1_{PROM}$	Individual value
$PZ2_{PROM}$	Typical value

Chapter 7

Measurements

The aim of the measurements was to confirm the simulation results for the LNA gain case. 48 components, two sub lots, was selected for characterization tests, all components from one of the Infineon Technologies production lines. Three different runs were successfully completed, each with a different Gp. It was an important point of itself that the exact same components were used for all runs, and that they were all run through the exact same test recipe. This was to have good control of the tests, and to isolate the effect of the LNA gain change.

7.1 Test Performed

Measurement runs with Gp=16 and Gp=10 are run, and also runs with Gp=25.6 were run. The intention of the last mentioned run was to check results consistency, meaning to see if the pressure measurement spread with Gp=25.6 was even smaller than for Gp=16. It was expected that Gp=10 gave the largest spread and Gp=25.6 gave the most. *Tab. 7.1* summarizes the tests completed. The recipe used performed both calibration and characterization, with calibration points (LT, HT, HP and AT) as given in *Tab. 3.1*, and characterization points as given in *Tab. 3.3*.

Calibration and test time for recipe 1088 was 15-16 hours.

Table 7.1: Calibration and characterization test runs. Gp settings, number of components in runs, and recipe number.

Gp	No of components in run	Recipe no
Gp=10	48	1088
Gp=16	47	1088
Gp=25.6	47	1088

7.2 Equipment Used

Prototype test equipment at Infineon Technologies were used for measurements with the intention of confirming the effect of LNA gain change. Test recipes and data logging were managed from the control equipment. The temperature chamber had a pressure chamber inside (*Fig. 7.1(b)*). In this inner chamber there was a PCB holding sockets for one sublot (24) of sensors. Hardware was wired from from each sensor sockets on the sensor board via connectors, all the way out to the test control equipment.

When tests were prepared there was always placed a pressure resistant lid (not visible on the figure) on the pressure chamber to seal it from the rest of the temperature chamber volume. The setup made it feasible to change pressure and temperature with high precision within the range of 100 kPa to 1500 kPa and -40 to 125 °C, according to test recipe (1088), within a fairly short time.

Flexible air supply tubes for the pressure chamber raised and lowered pressure according to controls. A fan mounted on the back wall of the temperature chamber made the temperature change in the volume fast.

(a) Temperature chamber and control equipment.

(b) Pressure chamber inside temperature chamber.

Figure 7.1: Test equipment used.

Chapter 8

Results

8.1 Simulation Results

8.1.1 ADC model

Verification of Random Normal Distribution Generator

The Excel function STDAV() was used to verify the spread on the generated series. The generator was set up to give a mean value (μ=0) and a spread (σ=1) and the deviation from it should not be too large to ensure a good approximation to the normal distribution. *Fig. 8.1* shows the result for 2500 generated signals. *Tab. 8.1* shows μ and σ verifications for five successive series generated, with 1000, 2500 and 5000 signals. *Tab. A.1* shows an extensive table for generated ADC input signals (Three 2500 series and three 5000 series).

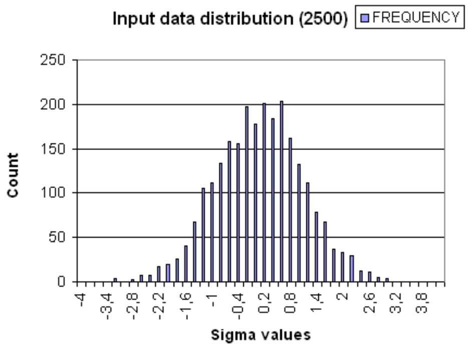


Figure 8.1: Example of signal distribution generated by the Random Normal Distribution Generator (2500 signals).

It could be seen that the mean and spread values for the generated 1000, 2500 and 5000 sensor die series differed from each other. The mean and spread deviations were smallest (and best) for the 5000 series and largest for the 1000 series.

As a measure for how far from perfect the generated series were it was taken a closer look at the values. A chosen measure in this relation was to consider the *average value of deviation* for mean and spread values. This was a measure for the variations regardless of direction of deviation. The absolute values of deviation from target values are summed and divided by the number of series (5), as shown in *Tab. 8.2*.

Table 8.1: Verification of mean and spread values from Random Normal Distribution Generator.

(a) Mean and spread for 1000 samples.

μ	σ
0,0192	0,9806
0,0281	0,9963
0,0404	1,0220
-0,0180	1,0199
0,0280	1,0169

(b) Mean and spread for 2500 samples.

μ	σ
-0,0166	1,0234
-0,0323	1,0091
-0,0197	1,0057
0,0129	1,0076
0,0013	0,9998

(c) Mean and spread for 5000 samples.

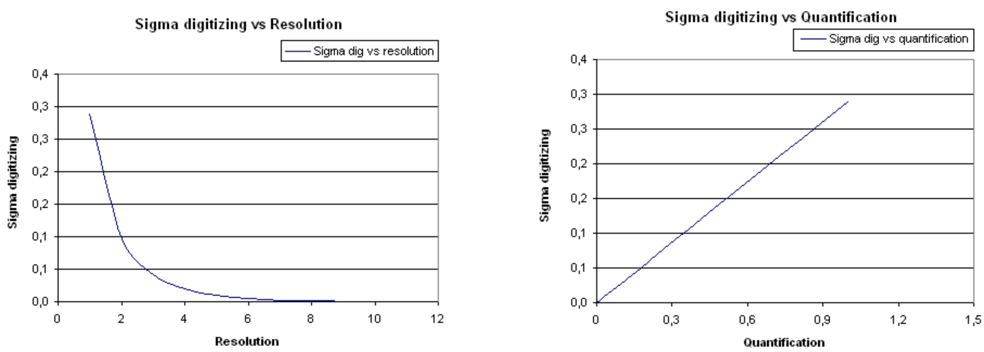
μ	σ
0,0019	0,9983
0,0331	1,0110
0,0058	0,9912
0,0210	1,0001
0,0148	0,9987

Table 8.2: Average deviation for mean and spread values of Random Normal Distribution Generator.

Parameter / no of generated signals	1000	2500	5000
Average deviation from μ=0	0,027	0,017	0,015
Average deviation for σ=1 (%)	1,6	0,9	0,5

Error Contributions from ADC Quantization

The formula of *Eq. 4.9* describes the error contribution from the ADC quantization. Calculations based on the different steps in the simulation model show that the contribution has a non-linear relation to resolution, and a linear relation to quantization (Fig. 8.2).



(a) Contribution to spread as function of resolution.

(b) Contribution to spread as function of quantization.

Figure 8.2: Spread contribution from ADC quantization.

Comparing Simulated and Calculated Error Contributions from ADC Quantization

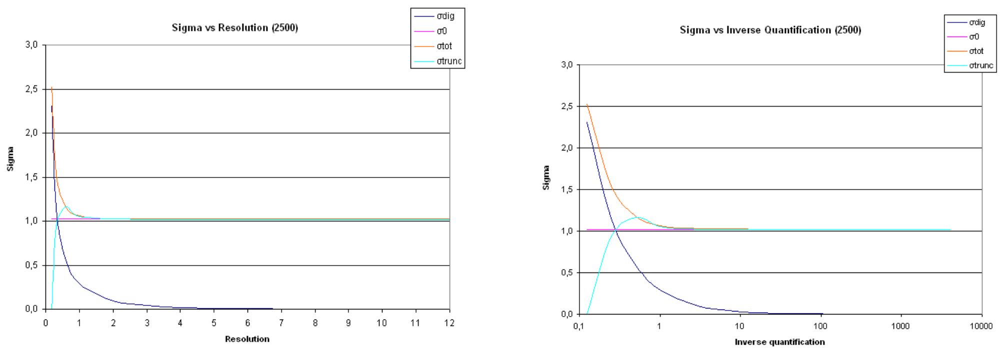
The ADC simulation model verifies the theory for quantization and its contribution to spread. *Fig. 8.3* shows 4 different σ values as a function of resolution and as a function of inverse quantization, where:

- σ_0 is the calculated standard deviation of the ADC input signal

- σ_{dig} - with *dig* for digitizing - is the spread contribution from ADC quantization

- σ_{trunc} - with *trunc* for truncation (actually round off) - is the result of the traditional way of calculating standard deviation for normal distribution errors

- σ_{tot} is the result of calculating standard deviation according to formulas for combining sources of normal distribution errors and quantization errors



(a) Sigma as function of quantization. (b) Sigma as function of inverse quantization.

Figure 8.3: Spread in ADC output in terms of standard deviations.

8.1.2 Sensor Model

Sensor model simulations showed ADC quantization errors at different ADC resolutions and LNA gains, and coefficient round off errors at different LNA gains.

Choosing ADC IDEAL confirmed no error contribution from ADC quantization, and choosing all coefficients IDEAL confirmed no error contributions from coefficient round offs.

Tab. 8.3 shows simulated ADC quantization errors for resolutions down to 10.

Table 8.3: Result of simulated ADC quatization errors. LNA gain 16 to 10. Values in kPa. Only highest values shown. (2500 sensors simulated)

ADCres	LNA 16	LNA 10	Error relation	Comment
12	±0.50	±0.88	1.8x worse	@ T_{in}= 125 °C
11	±1.1	±1.7	1.5x worse	@ T_{in}= 125 °C
10	±2.1	±3.4	1.6x worse	@ T_{in}= 125 °C

Since ps1, ps2 and pz2 was kept fixed and thus gave no variation in the corresponding PROM coefficients ($PS1_{PROM}$, $PS2_{PROM}$, and $PS1_{PROM}$), it was most interesting to consider round off errors for $PS0_{PROM}$, $PZ0_{PROM}$, and $PZ1_{PROM}$. The round off errors from $PS0_{PROM}$, $PZ0_{PROM}$, and $PZ1_{PROM}$ are listed in *Tab. 8.4* for LNA gain 16 and 10. Values are as they contribute in error in the calculated pressure, P_{calc}, in kPa.
More simulation results of ADC quantizations and coefficient round offs are found in *A.2.3*.

8.1.3 Process Model

It was seen that the sensors were not possible to calibrate if all sensor parameters were considered un-correlated and sensor die parameter specification reflect 6 sigma values. This

Table 8.4: Result of simulated PROM coefficients round off errors. LNA gain 16 to 10. Values in kPa. Only highest values shown. (2500 sensors simulated)

PROM coefficients	LNA 16	LNA 10	Error relation	Comment
$PS0_{PROM}$	±0.94	±0.63	1.5x better	@ P_{in}=1600 kPa
$PZ0_{PROM}$	±0.13	±0.19	1.5x worse	@ All P & T
$PZ1_{PROM}$	±1.38	±2.19	1.6x worse	@ T_{in}= 125 °C

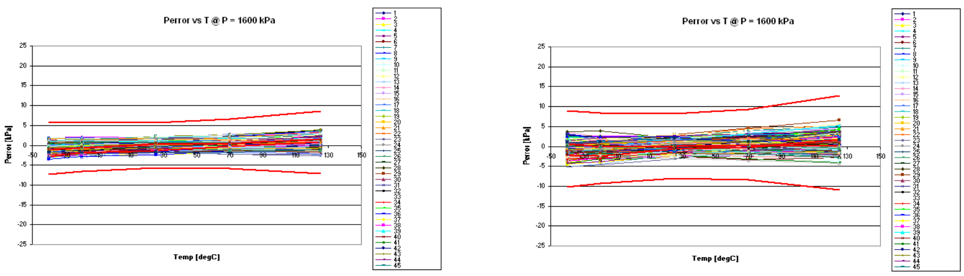
Table 8.5: Perror contribution from CALCPROM process. LNA gains 16 and 10. ADCres from 12 down to 10. Largest error only. (2500 simulation series)

LNA gain	ADCres	Perror [kPA]	LNA gain	ADCres	Perror [kPA]
16	12	±4	10	12	±6
16	11	±6	10	11	±9
16	10	±11	10	10	±20

simply gave very large deviation on pressure measure accuracy when attempted.

Setting $PS1_{CALCPROM}$, $PS2_{CALCPROM}$ and $PZ2_{CALCPROM}$ values fixed, however made the method work well.

Different ADC resolutions were set and simulations run to calculate CALCPROMs. Calculated values were rounded to integers as is inevitable, and characterization runs were performed to verify the calibration process. The characterization pressure and temperature was set at the same values as used in the sensor model, described in *6.2*. Error from ADC quantization at different LNA gains and ADC resolutions are shown in *Fig. 8.4, 8.5 and 8.6*.



(a) LNA 16.　　(b) LNA 10.

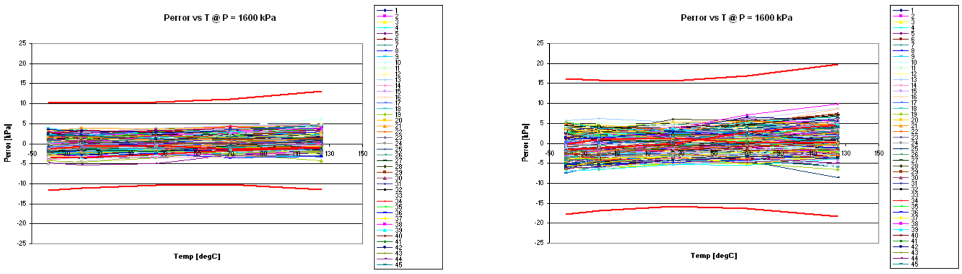
Figure 8.4: Perror @ LNA gain 16 and 10 for PROM CALC process. ADCres=12

8.2 Measurement Results

8.2.1 Test to investigate the effect of LNA gain change

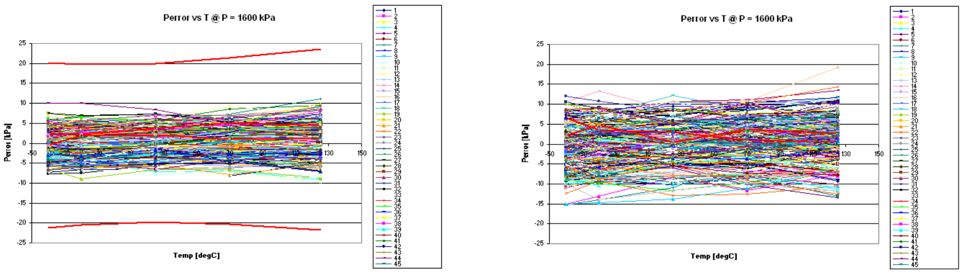
Sensor measurements were done to investigate the effect of LNA gain change. They can be summarized as:

- A total amount of 48 components were selected for tests. These were calibrated and verified with Gp=10, Gp=16 and Gp=25.6



(a) LNA 16 (b) LNA 10.

Figure 8.5: Perror @ LNA gain 16 and 10 for PROM CALC process. ADCres=11



(a) LNA 16. (b) LNA 10.

Figure 8.6: Perror @ LNA gain 16 and 10 for PROM CALC process. ADCres=10

- 7 components showed freak, outlier tendencies, or missed certain measurement results, and was thus taken out before analysis

- This left 41 components for analyzing and confirming the effect of going from Gp=16 to Gp=10

Tab. 3.5 indicate that most of the coefficients are expected to change when Gp changes (as Gp contributes in the scaling of 4 of the 6 PROM coefficients).

Changing Gp gave 4 new PROM coefficient each time as 4 PROM coefficient scalings are dependent of Gp.

Chapter 9

Discussions

9.1 Simulation Results

9.1.1 ADC Model

The Random Normal Distribution Generator was made first time for the ADC model and therefore its results are discussed here.

There was seen a significant difference for the Random Normal Distribution Generator in terms of average deviation from target for mean and spread values when changing the number of signals generated (*Tab. 8.2*). The improvement from 1k to 2.5k sensor die signals generated was much larger than the improvement from 2.5k to 5k. The improvement from 1k to 2.5k was from 2.7 to 1.7 % for average deviation of μ, and from 1.6 to 0.9 % for average deviation of σ. From 2.5 to 5k the same improvements was only from 1.7 to 1.5 % and 0.9 to 0.5 % respectively. Based on these findings it was decided to proceed making the sensor, process and final model with 2.5k sensor simulations.

Simulation results for σ_0, σ_{dig}, σ_{trunc}, σ_{tot} are shown in *Fig. 8.2*. σ_0 (pink line) verifies that the spread of the ADC input signals is at σ=1, being independent of resolution/inverse quantization. σ_{dig} (blue line) is making its appearance only at lower resolutions or lower values of inverse quantizations (as expected). Its contribution is given by the formula in *Eq. 4.9*, and it has an inverse, non-linear dependency to resolution/inverse quantization. σ_{tot} (orange line) is the calculated spread according to the formula given in *Eq. 4.7*, with σ_0 and σ_{dig} inserted (as shown in Calc. 9.1).

$$\sigma_{tot} = \sqrt{\sigma_0^2 + \sigma_{dig}^2} \tag{9.1}$$

σ_{trunc} (cyan line) is the calculated spread directly performed on the quantized ADC output signal by usage of the formula for normal distributions (*Eq. 4.5*). For the higher resolutions/higher inverse quantizations this line follows the σ_0 the same way as σ_{tot} does. For lower resolutions/lower inverse quantizations it raises before it again is reduced when the coarse quantizations in the ADC output signal gives less and less variation in the output signal. σ_{trunc} crosses the σ=1 line at $\approx$ 0,3 on the x-axis of the inverse quantization chart, corresponding to a resolution $<$ 1. At lower resolutions/inverse quantizations the coarse quantizations makes the σ_{trunc} go in direction of 0, naturally, because there is not spread left in the signal.

The results shown on the plots of σ_0, σ_{dig}, σ_{trunc}, σ_{tot} confirms:

- That the contribution to spread from quantization becomes more and more significant with reduced resolution/increased quantization. This is as expected. To see any significant effect of the quantization, however, the resolution must come down to $\approx$ 4-5 bits when looking at the contribution isolated, and down to 2 bits or less to see it when combined with the normal distribution already in the quantized output signal.

- The plots confirms also that the difference between the methods of calculating spread on quantized ADC outputs is just minor. The cyan line for the traditional way of calculating standard deviation, σ_{trunc}, of normal distributions follows the orange line, σ_{tot}, for how to add several independent contributions of spread.

9.1.2 Sensor Model

Simulation results confirm ADC quantization to increase with decreased resolution.

The quantization was largest in value at the highest temperatures because the pressure sensitivity is slightly decreasing with temperature, and since the quantization is larger on a reduced ADC input signal.

As expected, and shown from simulation results of *Tab. 8.3*, it was confirmed that the relation between ADC quantization error and LNA gain was directly dependent. Reducing the LNA gain from 16 to 10 increased the quantization errors by the same factor, i.e. $\approx$ 1.6. The larger the PROM values, the smaller the round off errors, and vica versa. This means if the LNA gain reduction effects the scaling of a coefficient and making it smaller - it will result in larger round of errors in the calculated pressure. Scaling of each PROM coefficients is according to *Tab. 3.5.* The reduction in LNA gain gave a simulated round off error which were 1.5x smaller for $PS0_{PROM}$.

The calculation for $PS0_{PROM}$ and its scaling is shown in *Eq. 9.2.* The equation shows that the reduced Gp give a larger PSO_{PROM}, and thus confirms the reduced round off of 1.5x for this PROM coefficient. 1.5x is close to the expected 1.6x error reduction dictated by the theory, and thus it is an acceptable confirmation.
$PS0_{PROM}$ results in the largest round off error at the highest pressures since it is multiplied with the raw data and the rest of the expression for compensated pressure according to *Eq. 3.9.*

$PZ0_{PROM}$ is neither temperature or pressure dependent since it is not multiplied with any temperature or pressure.
$PZ1_{PROM}$ is first degree temperature dependency of zero point and multiplied with temperature, and therefore give the largest round off error at the highest temperatures. (125 °C is longer away from 25 °C than -40 °C, and therefore the error was smaller at -40 °C.) The fact that the scaling of $PZ1_{PROM}$ were already not optimized to use a large part of the availble 8 bit signed, made round off errors for this PROM coefficient the most significant. At LNA gain 16 $PZ1_{PROM}$ operates between -24 and 24 of the available -128 to 127 (signed 8 bit), while with LNA gain 10 only from -15 to 15.
$PZ1_{PROM}$ round off error could be reduced by a factor of 8 by scaling it optimal. This corresponds to a reduction in error contribution from maximum $\pm$ 2.19 to maximum $\pm$ 0.27 kPa for 2.5k simulation results. Comparing 2.19 kPa with the pressure measurement specification limits for the heavy vehicle TPM sensor in the temperature range 50 to 125 °C, $\pm$ 30 kPa tells that today's $PZ1_{PROM}$ round off error is $\approx$ 7 % of the specification alone in the worst corner.

$$PSO_{PROM} = \frac{12^{12}}{ps0 \cdot Gp \cdot G12 \cdot Rp} \tag{9.2}$$

The scalings of $PZ0_{PROM}$ and $PZ0_{PROM}$ are linearly dependent of Gp, also according to *Tab. 3.5.* These PROM coefficient calculations are also shown in *Eq. 9.3* and *Eq. 9.4*, showing that the reduced LNA give reduced values for both $PZ0_{PROM}$ and $PZ0_{PROM}$. This confirms the simulation results showing increased error by 1.5x and 1.6x for the two PROM coefficients respectively. This is close to (and directly at for $PZ0_{PROM}$) the expected increase of 1.6x given by the formulas, and thus an acceptable confirmation.

$$PZO_{PROM} = pz0 \cdot Gp \cdot G12 \tag{9.3}$$

$$PZ1_{PROM} = pz1 \cdot Gp \cdot G12 \tag{9.4}$$

9.1.3 Process Model

Results of ADC quantization showed increased quantization with decreased ADC resolution as expected. ADC quantization at LNA gain 10, and ADC resolution 12 was confirmed comparable with ADC quantization at LNA gain 16, ADC resolution 11. This indicate that one should consider increasing the resolution one step for the heavy vehicle TPM sensor with LNA gain 10 to obtain about the same quantization error as when calibrating the TPM heavy vehicle sensor at LNA gain 16 (before the LNA gain reduction).

9.2 Measurement Results

Herein come the discussion of the measurement results.

Chapter 10

Conclusion and Recommendations

It was confirmed that a reduction of Gp from 16 to 10 results gives a larger accuracy spread for the pressure sensor. This was confirmed in simulations, and also in measurements. At this point both simulation and measurement results are very consistent. In measurements the exact same 41 sensors were run with the exact same test recipe, except for programming the sensors with different Gps (10, 16 and 25.6). The results showed reduced capability, and this is basically because:

- Reduced Gp gives larger ADC quantization errors. The smaller the ADC input signals, with the same number of quantization steps, the larger the quantization errors.

- Reduced Gp gives larger quantization errors in pressure compensation, caused by larger round offs errors in PROM coefficients. Four of six coefficients, $PS0_{PROM}$, $PZ0_{PROM}$, $PZ1_{PROM}$, and $PZ2_{PROM}$, are scaled mathematically directly by Gp, and thus a reduction of Gp increase round off errors for all of these.

  $PZ1_{PROM}$ is giving the largest contribution to round off errors in pressure measurement results.

  When decreasing the LNA gain from 16 to 10 for the heavy vehicle TPM sensor the $PZ1_{PROM}$ operating range was decreased by the factor 1.6, from -24 to 24 for LNA gain 16, down to -15 to 15 for LNA gain 10. $PZ1_{PROM}$ is a 8 bit signed value, with an available range from -128 to 127, meaning that the round off error from it could be reduced by a factor of 8 by scaling it optimal. This corresponds to a reduction in error contribution from maximum $\pm$ 2.19 to maximum $\pm$ 0.27 kPa for 2.5k simulation results. Comparing 2.19 kPa with the pressure measurement specification limits for the heavy vehicle TPM sensor in the temperature range 50 to 125 °C, $\pm$ 30 kPa tells that today's $PZ1_{PROM}$ round off error is $\approx$ 7 % alone in the worst corner.

  Scaling the $PZ1_{PROM}$ range 8x from todays range would make it from -120 to 120, reflecting 6 sigma values for sensor parameter variations, and still leave a guard band out to min and max values of -128 to 127. The pressure capability is not likely much effected of the non-optimized $PZ1_{PROM}$, however is recommended to consider optimal PROM coefficient scalings for future product to ensure minimal round off errors and optimized measurement performance.

Results of ADC quantization showed increased quantization with decreased ADC resolution as expected. ADC quantization at LNA gain 10, and ADC resolution 12 was confirmed comparable with ADC quantization at LNA gain 16, ADC resolution 11. This indicate that one should consider increasing the resolution one step for the heavy vehicle TPM sensor with LNA gain 10 to obtain about the same quantization error as when calibrating the TPM heavy vehicle sensor at LNA gain 16 (before the LNA gain reduction).

It was confirmed by simulations and theoretical calculations that traditional ways of considering pressure accuracy is sufficiently accurate for evaluating the heavy vehicle TPM sensor capability. The regime where errors from ADC quantization become significant are not before reaching resolutions as low as 5-6 bits.

Chapter 11

Acknowledgements

Many thanks to my supervisor at Infineon Technologies SensoNor, Reidar Holm, for being a guide and taking part in our many meetings and discussions along the way, always being very helpful and wise. Also many thanks to my second supervisor, Per Øhlckers, at The Institute for Microsystem Technology, at The College of Vestfold, for helpful advices, and especially for his recommendations to report outline and report content.

Also many thanks to several colleagues at Infineon Technologies SensoNor having contributed in form of performing measurements, or in form of taking part in conversations and being helpful for during my project work.

Appendix A

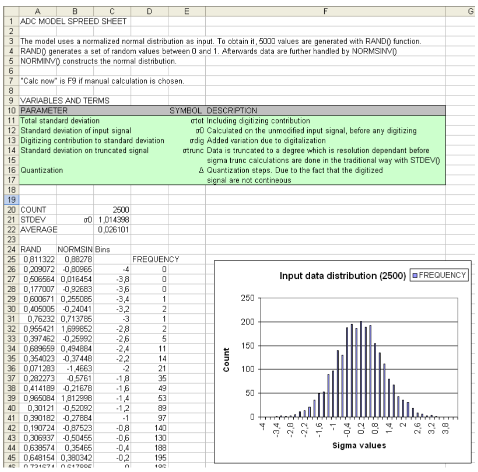
Simulation Details and Extensive Results

A.1 ADC Model

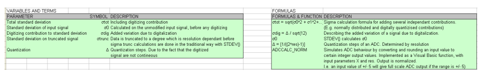
A.1.1 Formulas Used and Excel Printscreens

List of functions used in ADC model. Printscreens from excel simulation model pages (*Fig. A.1* below).

- RAND(), NORMSINV()
- STDEV(), AVERAGE()
- COUNT(), FREQUENCY()
- $ADCCALC_{NORM}()$ (As described in *Eq. 6.1*)



(a) Generation of ADC input signal



(b) Variables, terms and formulas

Figure A.1: Printscreens from ADC simulation model spread sheet.

A.1.2 Listed Results from Random Normal Distribution Generator

Random Normal Distribution Generator was first established and verified for the ADC model. The result table (*Tab. A.1*) is therefore listed in this section of the appendix.

Table A.1: Example of signal series generated by Random Normal Distribution Generator.

(a) 2500 signal series

Bin (σ)	#1	#2	#3
< -3.4	0	1	1
-3.4 to -3.2	0	4	2
-3.2 to -3.0	3	2	1
-3.0 to -2.8	1	5	2
-2.8 to -2.6	11	3	5
-2.6 to -2.4	5	11	11
-2.4 to -2.2	9	16	14
-2.2 to -2.0	25	20	21
-2.0 to -1.8	37	26	35
-1.8 to -1.6	47	38	49
-1.6 to -1.4	70	76	53
-1.4 to -1.2	88	65	89
-1.2 to -1.0	94	116	97
-1.0 to -0.8	134	134	140
-0.8 to -0.6	173	136	130
-0.6 to -0.4	179	195	188
-0.4 to -0.2	205	189	195
-0.2 to 0	219	198	186
0.0 to 0.2	183	209	201
0.2 to 0.4	195	200	189
0.4 to 0.6	167	177	192
0.6 to 0.8	172	154	155
0.8 to 1.0	118	138	135
1.0 to 1.2	95	110	111
1.2 to 1.4	77	92	80
1.4 to 1.6	53	52	68
1.6 to 1.8	50	43	43
1.8 to 2.0	29	32	35
2.0 to 2.2	22	21	31
2.2 to 2.4	16	21	18
2.4 to 2.6	13	8	9
2.6 to 2.8	5	5	6
2.8 to 3.0	3	2	3
3.0 to 3.2	1	1	4
3.2 to 3.4	1	1	1
> 3.4	0	0	0

(b) 5000 signal series

Bin (σ)	#1	#2	#3
< -3.4	4	1	2
-3.4 to -3.2	1	0	2
-3.2 to -3.0	3	2	2
-3.0 to -2.8	9	3	7
-2.8 to -2.6	13	2	13
-2.6 to -2.4	16	6	16
-2.4 to -2.2	25	16	36
-2.2 to -2.0	46	24	49
-2.0 to -1.8	53	35	74
-1.8 to -1.6	86	69	105
-1.6 to -1.4	130	105	141
-1.4 to -1.2	153	121	198
-1.2 to -1.0	242	189	205
-1.0 to -0.8	277	205	268
-0.8 to -0.6	314	260	301
-0.6 to -0.4	354	295	324
-0.4 to -0.2	388	360	356
-0.2 to 0	362	411	378
0.0 to 0.2	419	442	398
0.2 to 0.4	387	381	350
0.4 to 0.6	342	405	350
0.6 to 0.8	323	349	317
0.8 to 1.0	250	318	272
1.0 to 1.2	240	251	229
1.2 to 1.4	153	220	186
1.4 to 1.6	134	151	122
1.6 to 1.8	86	116	95
1.8 to 2.0	71	74	63
2.0 to 2.2	52	70	62
2.2 to 2.4	22	43	26
2.4 to 2.6	18	28	23
2.6 to 2.8	11	24	17
2.8 to 3.0	5	12	8
3.0 to 3.2	7	5	1
3.2 to 3.4	2	5	3
> 3.4	2	3	0

A.2 Sensor Model

A.2.1 Formulas Used and Excel Printscreens

List of functions used in sensor model, in addition to what already used in the ADC model.

- ROUND()
- IF()

Sensor parameters from IBS:

Parameter	Min	Nom	Max	Units	Description
ps0	27	32	37	uV/V/kPa	Sensitivity
ps1	0,0016	0,0021	0,0026	1/°C	Sensitivity, first order temperature dependancy
ps2	-5E-06	0	5E-06	1/C^2	Sensitivity, second order temperature dependancy
pz0	-4,4	0	4,4	mV/V	Zero point
pz1	-20	0	20	uV/V/°C	Zero point, first order temperature dependancy
pz2	-0,1	0	0,1	uV/V/°C^2	Zero point, second order temperature dependancy

IBS spec limits reflects number of sigmas:	6	Used for ps0, pz0 and pz1
Spec limits reflects number of sigmas:	infinity	To consider today's calc method.
		(Keeps ps0, pz0 and pz1 fixed)

Other parameters for heavy vehicle TPM sensor:

Parameter	Nom	Description
Gp	10	Global variable (selectable under "LNA, PROM and ADC selections")
Gp	16	Old heavy vehicle TPM sensor LNA gain
Gp	10	New heavy vehicle TPM sensor LNA gain
G12	2327,27273	Fixed part of ADC gain. Gadc = G12* 2^(res-12)
Rp	4	Global constant (fixed at 4.0).
ADCres	12	Global variable (selectable under "LNA, PROM and ADC selections")

LNA, PROM and ADC selections

LNA gain	16 (O)/ 10 (blank)
16 / 10	

PROM values	Real (R)/ Ideal (blank)
PSO_PROM	R
PS1_PROM	
PS2_PROM	
PZ0_PROM	R
PZ1_PROM	R
PZ2_PROM	

ADC	Real (R)/ Ideal (blank)
Quantification	R

ADC	Resolution (x)
12	x
11	
10	

Note: res 12, 11 or 10 must be chosen when ADC is not "ideal".
This is to have calc prom values made from raw data values.
(otherwize no calc_proms will be found)

Figure A.2: Sensor simulation model: Control sheet for adjusting ADC resolution, for turning ADC quantization ON/OFF, and for turning PROM coefficient round offs ON/OFF.

Valid ranges of calibration coefficients become:

Parameter	Min	Nom	Max	Units	Description	Comments
PS0	0,63	0,74	0,86	1/kPa	Sensitivity	Higher variation
PS1	0,0016	0,0021	0,0026	1/°C	Sensitivity, first order temperature dependancy	Lower variation
PS2	-5E-06	0	5E-06	1/C^2	Sensitivity, second order temperature dependancy	Lower variation
PZ0	-102	0	102		Zero point	Higher variation
PZ1	-0,5	0,0	0,5	1/°C	Zero point, first order temperature dependancy	Higher variation
PZ2	-2E-03	0	2E-03	1/°C^2	Zero point, second order temperature dependancy	Lower variation
PS0_PROM	1189	1375	1630	1/kPa	Sensitivity	Individually determined
PS1_PROM	105	138	170	1/°C	Sensitivity, first order temperature dependancy	Kept constant since the lower variation of PS1
PS2_PROM	-42	0	42	1/C^2	Sensitivity, second order temperature dependancy	Kept constant since the lower variation of PS2
PZ0_PROM	-410	0	410		Zero point	Individually determined
PZ1_PROM	-15	0	15	1/°C	Zero point, first order temperature dependancy	Individually determined
PZ2_PROM	-19	0	19	1/°C^2	Zero point, second order temperature dependancy	Kept constant since the lower variation of PZ2

Figure A.3: Sensor simulation model: Valid ranges for digitized sensor coefficients and valid ranges for PROM coefficients.

Sensors are simulated with the following measurement points:

Meas no	Pin	Units	Tin	Units	Comments
1	100	kPa	-40	°C	
2	100	kPa	-20	°C	LP, LT
3	100	kPa	25	°C	LP, AT
4	100	kPa	70	°C	LP, HT
5	100	kPa	125	°C	
6	657,5	kPa	-40	°C	
7	657,5	kPa	-20	°C	
8	657,5	kPa	25	°C	HP, AT
9	657,5	kPa	70	°C	
10	657,5	kPa	125	°C	
11	1600	kPa	-40	°C	
12	1600	kPa	-20	°C	
13	1600	kPa	25	°C	
14	1600	kPa	70	°C	
15	1600	kPa	125	°C	

ABOUT !
Truncations that can be seen by using the sensor model:
- Truncations for calculated coefficients
- Truncations for AD converting
(- The combinations of the above)

Figure A.4: Sensor simulation model: Simulated measurement points (pressures and temperatures.

A.2.2 Excel Code

Generating Sensor Die Parameters

For generating sensor die parameters the following code was used (example for ps0):

='Sensor model'!$C$3 + (NORMSINV(RAND())/'Sensor model'!$E$11)
*('Sensor model'!$D$3-'Sensor model'!$B$3)/2

Where:

C3 contains nominal ps0 value from sensor die documentation ([9])
E11 contains number of sigma values reflected for ps0 (set to 6)
D3 and B3 contains max and min values for ps0 respectively ([9])

The same method as used for generating ps0 was used for generating pz0 and pz1. ps1, ps2 and pz2, however, was set to constant typical values due to their low variations.

Generating Sensor Die Output

For generating pressure sensor die output signals the following code was used (example for vp_100_-40)):

='($B2*'Sensor model'!$B$43+$E2*1000+$F2*('Sensor model'!$D$43-25)+$G2
('Sensor model'!$D$43-25)^2)/(1+$C2('Sensor model'!$D$43-25)+$D2
*('Sensor model'!$D$43-25)^2)

Where:

B2, C2, D2, E2, F2 and G2 contains generated sensor die parameters
B43 contains simulated input pressure in kPa (100)
D43 contains simulated input temperature in °C (-40)

Units and scalings were used so that sensor die output signals were given in μV/V.

Generating Ideal ADC Raw Data Output

For generating ideal ADC raw data output the following code was used (example for Praw_100_-40):

=($BA2*'Sensor model'!$B$43+$BD2+$BE2*('Sensor model'!$D$43-25)+$BF2
('Sensor model'!$D$43-25)^2)/(1+$BB2('Sensor model'!$D$43-25)+$BC2
*('Sensor model'!$D$43-25)^2)

Where:

BA2, BB2, BC2, BD2, BE2 and BF2 contains digitized sensor die coefficients
B43 contains simulated input pressure in kPa (100)
D43 contains simulated input temperature in °C (-40)

Generating Quantized ADC Raw Data Output

For generating real, quantized, ADC raw data output the following code was used (example for Praw_100_-40)):

=ROUND(H2*'Sensor model'!$B$17*(2$^{'Sensormodel'!\$B\$22}$/1,76)/1000000;0)
*2$^{(12-'Sensormodel'!\$B\$22)}$

Where:

H2 contains sensor die output signal
B17 contains LNA gain
B22 contains ADC resolution

Generating Digitized Sensor Coefficients

For generating digitized sensor coefficients the following code was used (example for PSO):

=$B2*0,000001*'Sensor model'!B$17*'Sensor model'!B$20

Where:

B2 contains sensor die parameter, ps0
B17 contains LNA gain
B20 contains G12

The other digitized sensor coefficients are calculated in a similar way, with other scaling factors, according to *Tab. 3.5.*

Generating ideal PROM Coefficients

For generating ideal PROM coefficients the following code was used (example for PSO_{PROM_i}):

=2^{12}/(BA2*'Sensor model'!$B$21)

Where:

BA2 contains digitized sensor coefficient, PSO
B21 contains pressure resolution, Rp

The other ideal PROM coefficients are calculated in a similar way, with other scaling factors, according to *Tab. 3.5.*

Generating Truncated PROM Coefficients

For generating real,truncated, PROM coefficients the following code was used (example for PSO_{PROM}):

=ROUND(BG2;0)

Where:

BG2 contains the ideal PROM coefficient, PSO_{PROM_i}

The other PROM coefficients are truncated in the same way.

Calculating Ideally Compensated Pressure

For calculating ideally compensated pressure the following code was used (example for Pcomp_100_-40_i):

=\$BG2*(2^{-6})*(W2*(1+\$BH2*(2^{-16})*('Sensor model'!\$D\$43-25)+\$BI2*(2^{-23})
('Sensor model'!\$D\$43-25)^2)-(\$BJ2(2^{-2})+\$BK2*(2^{-5})*('Sensor model'!\$D\$43-25)+
\$BL2*(2^{-13})*($'Sensormodel'!\$D\$43 - 25)^2$))

Where:

BG2, BH2, BI2, BJ2, BK2 and BL2 contains the ideal PROM coefficients, PSO_{PROM_i}, $PS1_{PROM\_i}$, $PS2_{PROM\_i}$, PZO_{PROM_i}, $PZ1_{PROM\_i}$ and $PZ2_{PROM\_i}$

W2 contains the ideal raw data, $Praw\_100\_ - 40\_i$
D43 is the input pressure, P_{in}

Since all inputs are ideal for the ideally compensated pressure, with no ADC quantization, and no coefficient round off, the result is always exactly equal to the input pressure.

Calculating Truncated Compensated Pressure

For calculating truncated compensated pressure the following code was used (example for Pcomp_100_-40):

=ROUND(IF('Sensor model'!\$K\$6="R";\$BM2;\$BG2)*(2^{-6})
(IF('Sensor model'!\$K\$14="R";AL2;W2)(1+IF('Sensor model'!\$K\$7="R";\$BN2;\$BH2)
(2^{-16})('Sensor model'!\$D\$43-25)+IF('Sensor model'!\$K\$8="R";\$BO2;\$BI2)*(2^{-23})
('Sensor model'!\$D\$43-25)^2)-(IF('Sensor model'!\$K\$9="R";\$BP2;\$BJ2)(2^{-2})
+IF('Sensor model'!\$K\$10="R";\$BQ2;\$BK2)*(2^{-5})*('Sensor model'!\$D\$43-25)
+IF('Sensor model'!\$K\$11="R";\$BR2;\$BL2)*(2^{-13})*('Sensor model'!\$D\$43-25)^2));0)

Where:

K6, K7, K8, K9, K10, K11 are control cells for $PS0_{PROM}$, $PS1_{PROM}$, $PS2_{PROM}$, PZO_{PROM}, $PZ1_{PROM}$ and $PZ2_{PROM}$ selections. (By checking K6... K11 cells with "R" for "REAL", it is chosen to truncate the corresponding PROM coefficients, while leaving the cells open provides ideal coefficients)
BM2, BN2, BO2, BP2, BQ2, BR2 are truncated or REAL PROM coefficients
BG2, BH2, BI2, BJ2, BK2, BL2 are ideal coefficients
K14 is a control cell for turning ADC quantization ON/OFF. (R for "REAL" turns it on)
AL2 provides quantized ADC raw data results, W2 provides ideal ADC raw data results without any quantization)
D43 contains input temperature

These above described selections make it possible to look at error contributions isolated or in combination with each other. (E.g. it is possible to look at spread caused by $PZ1_{PROM}$ round offs isolated by setting all other coefficient control cells and the ADC control cell open (blank), giving no round off error from any other PROM coefficient and ADC quantization error.)

Calculating Ideal Measured Pressure

For calculating measured pressure the following code was used (example for Pout_100_-40_i):

=CE2*2^{-6}*'Sensor model'!$B21$

Where:

CE2 contains the ideal compensated pressure
B21 contains the pressure resolution (equal to 4.0 the heavy vehicle TPM sensor)

Calculating Measured Pressure

For calculating measured pressure the following code was used (example for Pout_100_-40):

=CT2*2^{-6}*'Sensor model'!$B21$

Where:

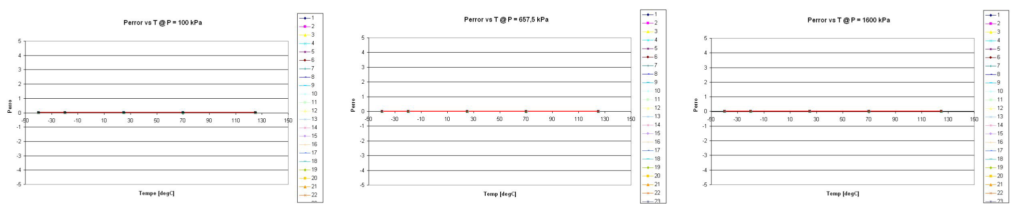
CE2 contains the truncated compensated pressure
B21 contains the pressure resolution (equal to 4.0 for the heavy vehicle TPM sensor)

A.2.3 Extensive Collection of Sensor Simulation Results

When changing LNA gain the largest difference in results were seen when going from 25.6 to 10. Therefore these results are listed herein.

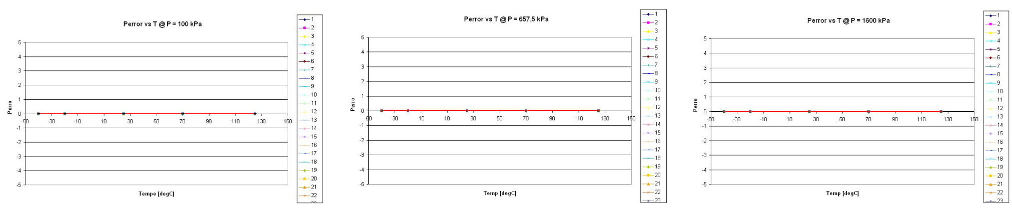
2500 sensors were simulated. Perror vs T for 250 of them, and max and min values (in bold red) for all of them, are graphically represented in each plot.

ADC Round off errors from *Fig. A.5 to A.12*, and coefficient Round off errors from *Fig. A.13 to A.28*



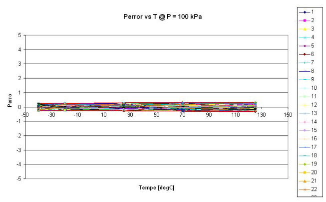
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.5: Perror vs T plots. Ideal ADC behaviour (Round off = OFF). Gp=25.6.

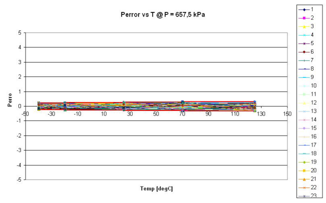


(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

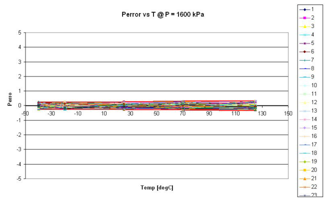
Figure A.6: Perror vs T plots. Ideal ADC behaviour (Round off = OFF). Gp=10.



(a) P_{in}=100 kPa

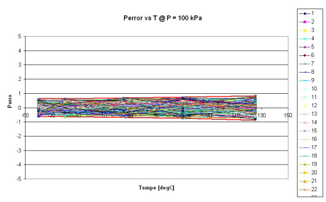


(b) P_{in}=657.5 kPa.

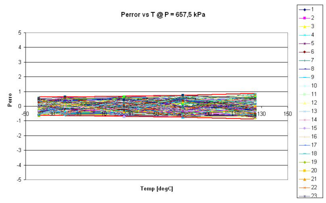


(c) P_{in}=1600 kPa.

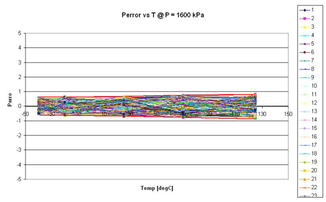
Figure A.7: Perror vs T plots. Real ADC behaviour (Round off = ON, ADCres=12). Gp=25.6.



(a) P_{in}=100 kPa

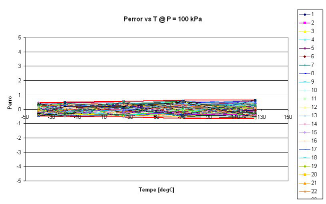


(b) P_{in}=657.5 kPa.

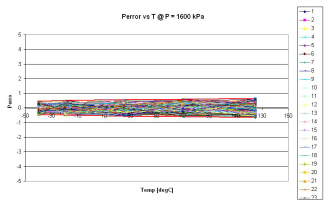


(c) P_{in}=1600 kPa.

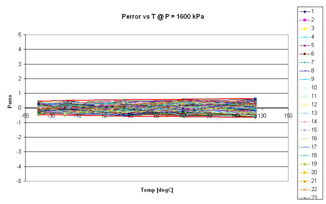
Figure A.8: Perror vs T plots. Ideal ADC behaviour (Round off = ON, ADCres=12). Gp=10.



(a) P_{in}=100 kPa

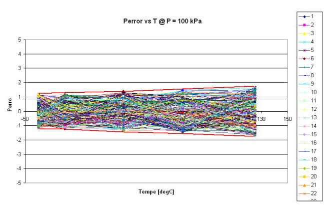


(b) P_{in}=657.5 kPa.

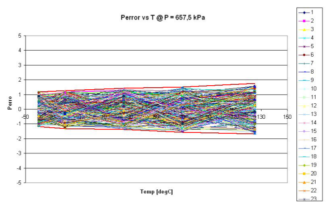


(c) P_{in}=1600 kPa.

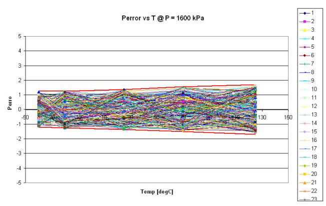
Figure A.9: Perror vs T plots. Real ADC behaviour (Round off = ON, ADCres=11). Gp=25.6.



(a) P_{in}=100 kPa

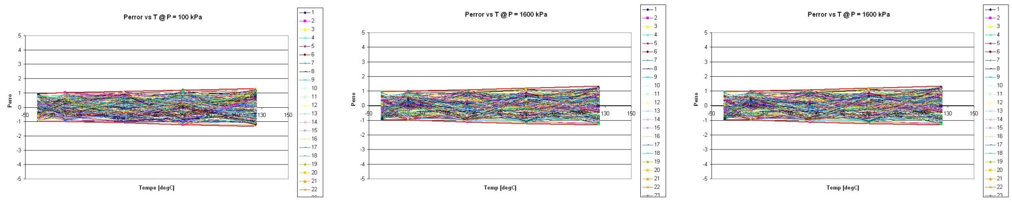


(b) P_{in}=657.5 kPa.



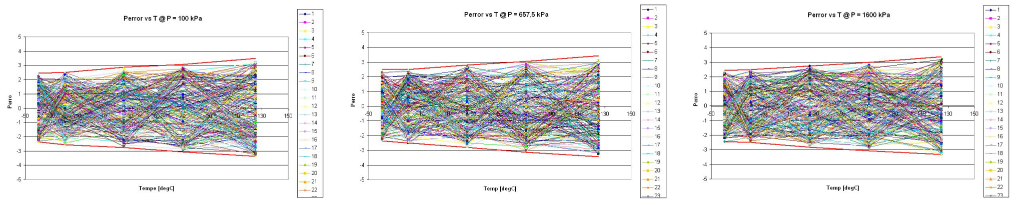
(c) P_{in}=1600 kPa.

Figure A.10: Perror vs T plots. Ideal ADC behaviour (Round off = ON, ADCres=11). Gp=10.



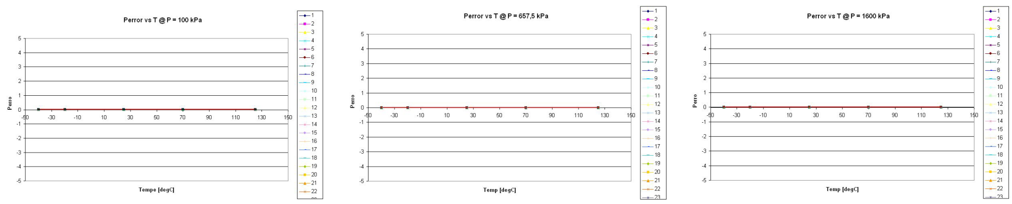
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.11: Perror vs T plots. Real ADC behaviour (Round off = ON, ADCres=10). Gp=25.6.



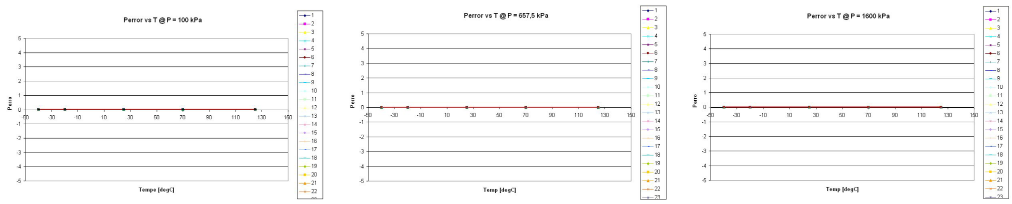
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.12: Perror vs T plots. Ideal ADC behaviour (Round off = ON, ADCres=10). Gp=10.



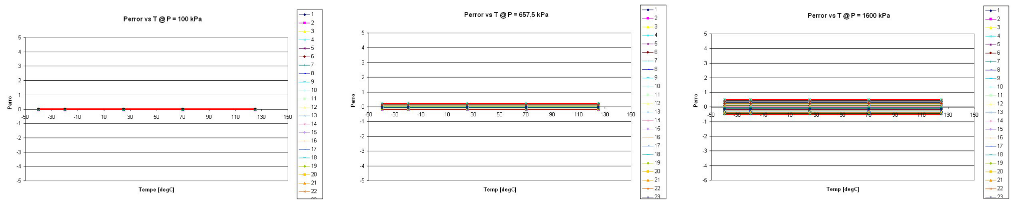
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.13: Perror vs T plots. Ideal coefficients (Round off = OFF). Gp=25.6.



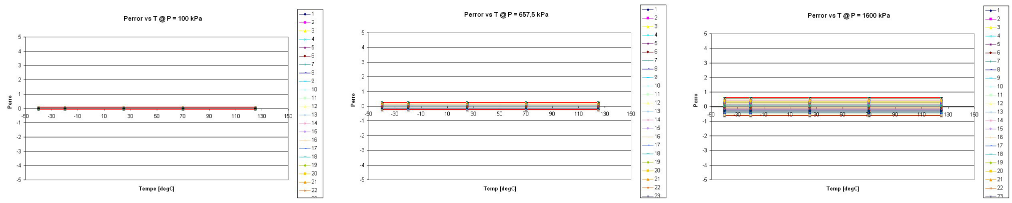
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.14: Perror vs T plots. Ideal coefficients (Round off = OFF). Gp=10.



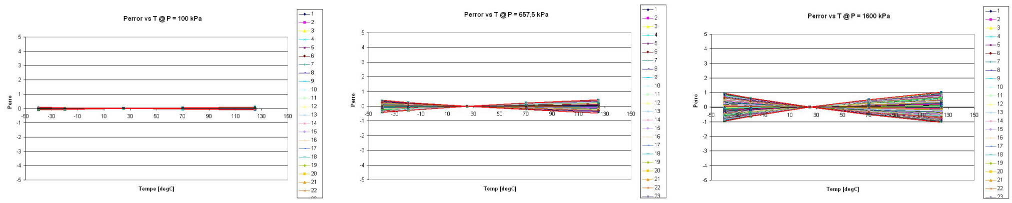
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.15: Perror vs T plots. Real coefficients (Round off = ON for PSO_{PROM}). Gp=25.6.



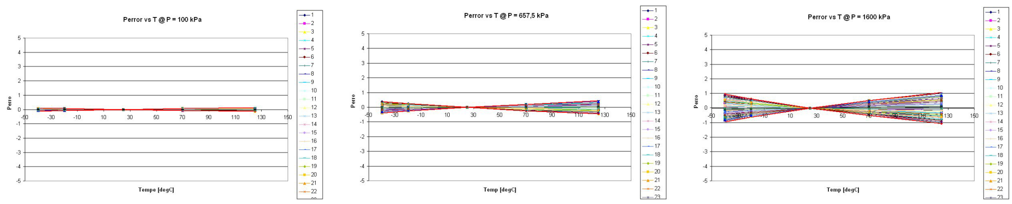
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.16: Perror vs T plots. Real coefficients (Round off = ON for PSO_{PROM}). Gp=10.



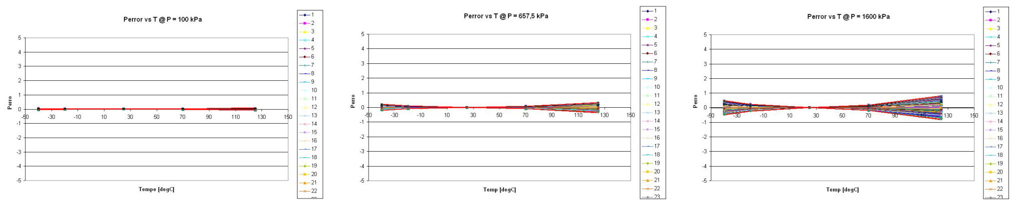
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.17: Perror vs T plots. Real coefficients (Round off = ON for $PS1_{PROM}$). Gp=25.6.



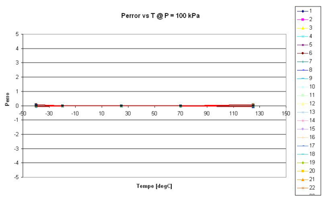
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.18: Perror vs T plots. Real coefficients (Round off = ON for $PS1_{PROM}$). Gp=10.

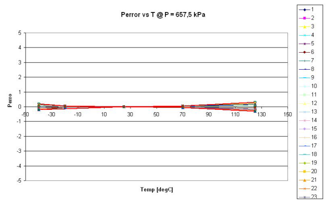


(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

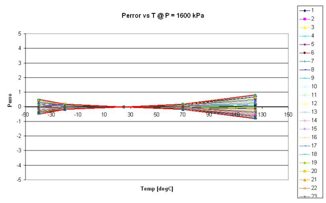
Figure A.19: Perror vs T plots. Real coefficients (Round off = ON for $PS2_{PROM}$). Gp=25.6.



(a) P_{in}=100 kPa

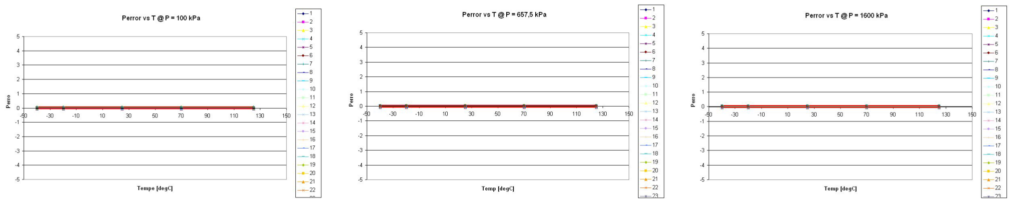


(b) P_{in}=657.5 kPa.



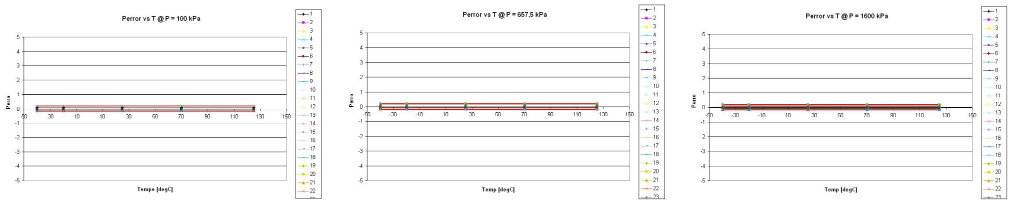
(c) P_{in}=1600 kPa.

Figure A.20: Perror vs T plots. Real coefficients (Round off = ON for $PS2_{PROM}$). Gp=10.



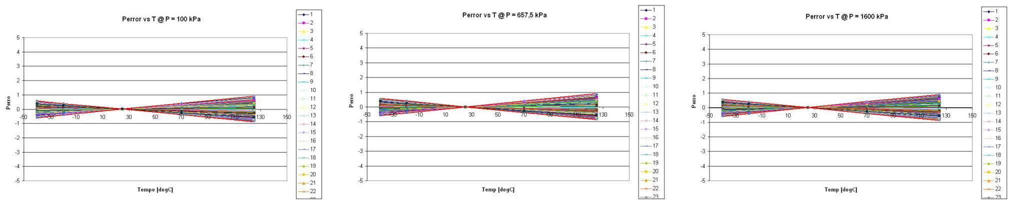
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.21: Perror vs T plots. Real coefficients (Round off = ON for $PZ0_{PROM}$). Gp=25.6.



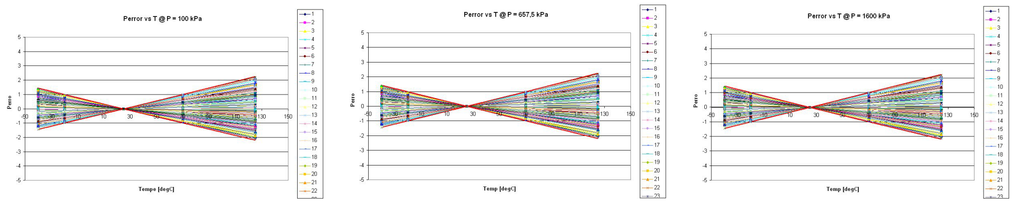
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.22: Perror vs T plots. Real coefficients (Round off = ON for $PZ0_{PROM}$). Gp=10.



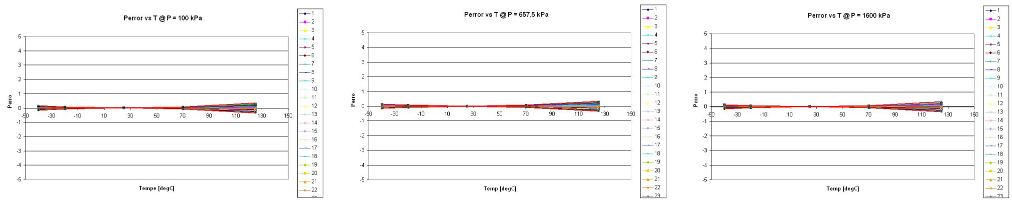
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.23: Perror vs T plots. Real coefficients (Round off = ON for $PZ1_{PROM}$). Gp=25.6.



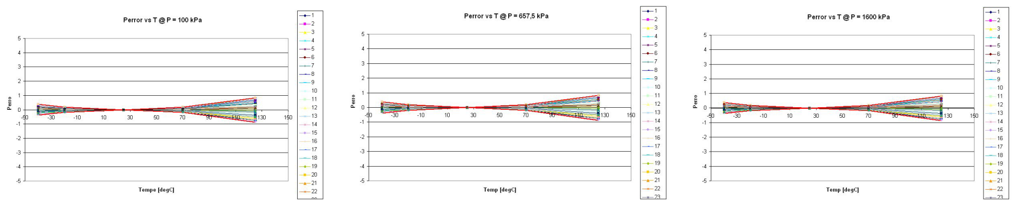
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.24: Perror vs T plots. Real coefficients (Round off = ON for $PZ1_{PROM}$). Gp=10.



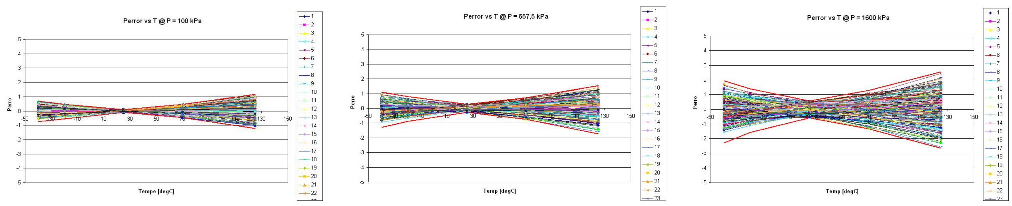
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.25: Perror vs T plots. Real coefficients (Round off = ON for $PZ2_{PROM}$). Gp=25.6.



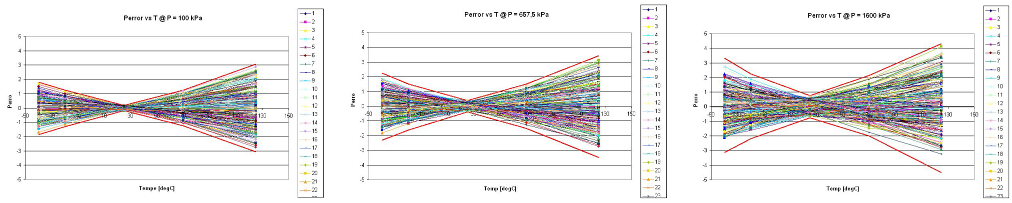
(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.26: Perror vs T plots. Real coefficients (Round off = ON for $PZ2_{PROM}$). Gp=10.



(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.27: Perror vs T plots. Real coefficients (Round off = ON for ALL coefficients). Gp=25.6.



(a) P_{in}=100 kPa (b) P_{in}=657.5 kPa. (c) P_{in}=1600 kPa.

Figure A.28: Perror vs T plots. Real coefficients (Round off = ON for ALL coefficients). Gp=10.

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