Background noise assessment of low-cost vibration sensors in precision manufacturing applications

A. Iqbal, N. S. Mian, A. P. Longstaff, S. Fletcher
Centre for Precision Technologies, University of Huddersfield, Queensgate, Huddersfield HD1 3DH, United Kingdom
Email: ali.iqbal@hud.ac.uk

Abstract

Accurate, reliable, and consistent vibration measurements in manufacturing machines such as machine tools, form the basis for predictive maintenance and condition monitoring applications Recent advancements in Micro Electro-Mechanical Systems (MEMS) has led to a rapid adoption of low-cost industrial grade MEMS vibration sensors in contrast to traditional high-cost Integrated Electronics Piezo-Electric (IEPE) accelerometers which have been typically used in precision manufacturing setups. However, low-cost MEMS accelerometers are subject to various deterministic and stochastic noise phenomenon which often limits their performance especially when subject to low acceleration conditions. Preliminary work has been performed for characterization of baseline errors and uncertainties of such low-cost triaxial vibration sensors to evaluate their viability in metrological applications for Industry 4.0. However, employment of low-cost MEMS sensors for long term vibration measurements requires assessment and quantification of time dependent progression of the noise and its effect. Methods such as Allan Variance which are based on regression analysis of entire time-domain sensor data provide effective modelling and systematic assessment of background noise in MEMS based sensors in accordance with IEEE 1293-2018 standard.

To evaluate the background noise in these low-cost industrial MEMS sensors, continuous long-term data was recorded on a vibrationally stable test bed while establishing traceability according to the ISO 16063-11:1999 and ISO 16063-21:2003 standards. Linear accelerometer analysis was conducted to quantify and characterize various types of noise and random effects contributing to the sensor measurements while ensuring input to the setup is lower than intrinsic noise of the sensors. This work attempts to model noise parameters of low-cost MEMS vibration sensors to mitigate the baseline errors and random noise for employment

in industrial manufacturing setups and smart condition monitoring applications. Results from this study will offer an improved framework for sensor stability through obtaining a low noise floor by a careful consideration of underlying random processes within metrology applications.

1 Introduction

Accurate, reliable, and consistent vibration measurements in manufacturing such as machine tools, form the basis for predictive maintenance and condition monitoring applications [1]. The rise of accelerometer sensors based on Micro Electro-Mechanical Systems (MEMS) technology have already found appreciation in wide area of vibration sensing setups e.g. building structures, remote power setups, smart cities etc [2] due to their lower cost, improved accuracy and digitalization aspects. This has led to a rapid adoption of such low-cost industrial grade MEMS vibration sensors , in contrast to the traditional high cost Integrated Electronics Piezo-Electric (IEPE) accelerometers which have been typically used in precision manufacturing setups [3]. Applications such as machine tool prognostics, smart machining and precision engineering often require low amplitude vibration measurements at low range of frequencies [4]. High sensitivity requirements in various applications of the vibration sensors not only involves estimating the optimum placement of sensors where attenuation to vibration is minimal but also choice of sensors with extremely low noise floor.
However, noise is ubiquitous to such low-cost MEMS sensors and form the source of significant errors in applications where measurement of vibrations with low amplitude and frequency is important. Subsequently, these errors can become more significant if they are progressive over long-term. Therefore, the employment of low-cost MEMS sensors for long term vibration measurements requires assessment and quantification of time dependent progression of the noise and its effect. The issue of noise also necessitates the characterization and modelling of noise-based error models to fulfil need for the required tolerances and accuracy in industrial applications, with the ultimate goal of denoising of sensor measurements [5]. The noise in MEMS vibration sensors consist of both deterministic and stochastic parts [6]. The deterministic errors are often contributed by constant bias (sensor offset), scaling errors, non-linearity and cross axis sensitivity which can be quantified via calibration techniques through establishing traceability [1]. While the stochastic part of the errors in such sensors is due to random phenomenon, the elimination of which, is challenging and requires rigorous modelling and quantification through stochastic techniques.
Several variance-based techniques have been devised for stochastic estimation of sensors noise e.g., Power Spectral Density (PSD), Autocorrelation Function (ACF), Kalman filtering, Allan Variance (AVAR) etc [7]. Out of the various methods Allan Variance which is based on regression analysis of entire time-domain sensor data provides simple and effective modelling technique through a systematic assessment of background noise in MEMS sensors [8]. Preliminary work has been performed for characterization of baseline errors and uncertainties of such low-cost triaxial vibration sensors to evaluate their viability in

metrological applications for Industry 4.0 [3]. This paper progresses to the next step and evaluates the background noise in these low-cost industrial MEMS sensors through implementation of Allan Variance method on measured static long term vibration data.

2 Background Noise Estimation

Noise is an ever-expanding area in engineering that poses practical problems and warrants further research. Noise can include both unavoidable intrinsic noises contributing to the system and noise of extrinsic nature due to operating conditions. Like all sensors and instruments the role of noise in MEMS has two important aspects, first is the sources which contribute to noise and secondly the practical limitations that result due to it [9]. It is a significant fact that noise limits the performance and degrades the measurements of many sensors systems. However, due to the design and size MEMS based accelerometers such noise problems can be acute especially at low values of input, thereby limiting the performance of systems, especially when operating under low acceleration conditions [9]. This accentuates the need for investigation of noise in precision manufacturing setups where the application requires to maintain tight tolerances. The current work focuses on identifying and modelling the background noise in MEMS vibration sensors. While a non-exhaustive list of the noise errors for MEMS can be drawn, this work would focus on the fundamental noise sources intrinsic to MEMS sensors as they can be the limiting factor for device performance in metrological applications.

2.1 Common types of noise in MEMS accelerometers

The most relevant noise errors encountered in MEMS that are being considered for evaluation as part of the work are presented below, with brief description.

2.1.1 Quantization

It is the noise caused due to Analog to Digital conversion (ADC) errors and relates to resolution of the sensor. With a greater resolution of ADC, the noise due to quantization would be smaller.

2.1.2 Velocity Random Walk (VRW)

VRW measures the error resulting after integrating accelerometer to get velocity measurements caused by white noise in the sensors.

2.1.3 Bias Instability (BI)

The source of BI is the electronics components susceptible to random flickering, which manifests as a bias over time. It also called flicker, pink or $1/f$ noise.

2.1.4 Sinusoidal Noise

The source of this noise is attributable to periodic environmental changes in the sensor measurements.

2.1.5 Rate Random Walk (RRW)

Rate random walk appears in acceleration measurements as a random drift rate

2.1.6 Rate Ramp (RR)

The source of this error is a linear long-term increase of the sensor's rate signal output. In contrast with others, it becomes deterministic in nature over time.
By now it is clear in many sensors that the nature of underlying noise is often unknown. In fact, several different noise sources may contribute simultaneously to corrupt the sensor signals. While, if correctly mathematically modelled tools such as auto-correlation function (ACF) and power spectral density (PSD) estimation can be used but if the noise errors are stochastic or random in nature, these methods do not suffice to characterize the underlying noise. In the next section, an effective method known as Allan variance (AVAR) sensor noise characterization will be introduced and discussed through developing its relationship with the noise terms identified earlier [10].

2.2 Allan Variance (AVAR) Method

Allan variance is a time-domain estimation of noise sources through linear accelerometer analysis. The resulting values characterize the noise by quantifying the spread in measurement values (or noise) across various time scales. Therefore, in simple terms the method offers an intuitive understanding of the evolution of noisy sensor signal over time. In general, the Allan variance, $\sigma_a^2\,(\tau)$, of a continuous time signal, $\Omega(t)$, is a function of a quantity called averaging time, τ, and is given by the following:

$$\sigma_a^2\,(\tau) = \frac{1}{2(N-2n)} \sum_{k=1}^{N-2n} [\bar{\Omega}_{k+1}(\tau) - \bar{\Omega}_k(\tau)]^2 \quad where\ n = \frac{\tau}{\Delta t}$$

Where, N is the total number of samples in the discretized signal, Δt is the sampling period and $\bar{\Omega}_k(\tau)$ can be shown as:

$$\bar{\Omega}_k(\tau) = \frac{1}{\tau}\int_{t_k}^{t_k+\tau} \Omega(t)dt\ \ , \Delta t \le \tau \le N\Delta t/2$$

Essentially, the results are obtained by dividing the sampled signals into clusters, $\bar{\Omega}_k(\tau)$, averaging over a duration,τ, and computing the variances among groups as a function of varying τ in a "non-overlapping" manner, since the clusters $\bar{\Omega}_k(\tau)$ do not overlap across time.
The different types of random processes can be examined by investigating the Allan variance plot. The Allan variance provides a means of identifying various noise terms that exist in the data as they appear in different regions of T. A typical Allan variance plot looks like that shown in Figure 1 [11]
This property permits easy identification of various random processes that exist in the data. A summary of various noise sources in their relationship with the AVAR plot can be seen in Table 1. If it can be assumed that the existing random processes are all statistically independent, then it can be shown that the Allan variance at any given τ is the sum of Allan variances due to the individual random processes at the same τ. This can be modelled mathematically as: -

$$\sigma_a^2\,(\tau) = \sigma_q^2(\tau) + \sigma_{rw}^2(\tau) + \sigma_{bi}^2(\tau) + \sigma_{rrw}^2(\tau) + \sigma_{rr}^2(\tau) + \cdots$$

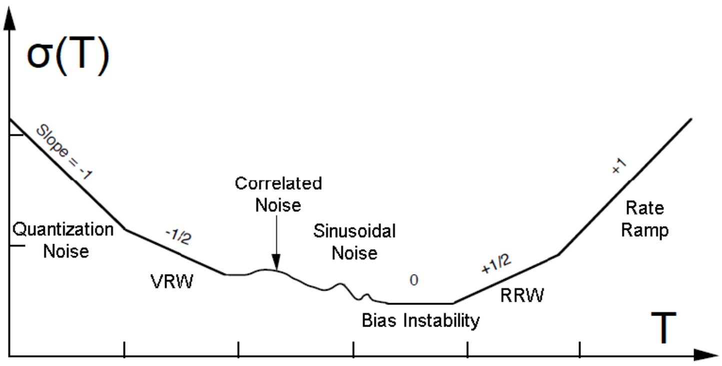

Figure 1 : Typical AVAR plot for MEMS sensors

Table 1: Summary of AVAR slopes for common noise processes [12]

Noise Source	Symbol	Slope (k)	Coefficient Units
Quantization	σ_q	-1	(m/s^2)
Velocity Random Walk (VRW)	σ_{rw}	-1/2	(m/s/√s)
Bias Instability (BI)	σ_{bi}	0	(m/s^2)
Acceleration Rate Random Walk (RRW)	σ_{rrw}	1/2	(m/s^2/√s)
Rate Ramp (RR)	σ_{rr}	1	(m/s^2/s)

3 Methodology

A simple scenario to estimate the sensor self-noise is modelling noise parameters when the input to the sensor is lower than the intrinsic noise. This can be observed by taking measurements on a location where the level of vibration is low and unaffected by background noise factors [13]. Another aspect to be ensured before data collection is to minimize the temperature variation as it can affect the stochastic characteristics of noise parameters to be estimated in low-cost MEMS sensors [14]. The background noise estimation and characterization tests for low-cost accelerometers was conducted by establishing traceability of the setup according to the ISO 16063-21 [15] and ISO 16063-11 [16] standards. These standards provide guidelines for calibration of vibration sensors by comparing their results to a reference transducer and laser interferometry. In this work, the methodology for noise characterization for MEMS based sensors was derived according to the IEEE-STD-1293-2018 [11] which identifies PSD and Allan Variance (AVAR) as key methods for the analysis of noise. However, the current work focuses solely on AVAR as an established technique for time domain analysis to model underlying random processes that give rise to the data noise in accordance with IEEE-STD-952-1997 [12] standard.

For the practical implementation of Allan Variance method to characterize different types and magnitudes of noise error terms in low-cost industrial MEMS sensors, a continuous long-term static test was conducted based on the aforementioned standards. The test was performed in a vibration-isolated and temperature-controlled environment for the duration of 60 hours. A detailed experimental setup and choice of sensors is explained in the next section.

3.1 Experimental Setup

An industrial grade tri-axial digital MEMS sensor (ADXL355) [17] was selected as a low-cost vibration sensor for modelling the noise parameters. While other MEMS sensors are available in the market at a lower price point [2], this (ADXL355) sensor provided high resolution (20-bit) on chip ADC along with required sensitivity for low amplitude measurements. The sensor also boasts ultralow noise features that may be expected from traditional accelerometers while with the added capability of providing the digital communication options (I2C/SPI) for convenient and configurable data acquisition modes. Key specifications for ADXL355 MEMS sensor are shown in Table 2. A tri-axial IEPE accelerometer (PCB 356A02) [18] was employed as a reference transducer in the experiment. A Renishaw XL-80 laser interferometer [19] was used as traceable reference in acceleration measurement mode for benchmarking the vibrational stability of the setup. The sensors were mounted on a 5 mm aluminium plate and secured using bolts, while the sensor cables were secured using adhesive clamps minimizing transmission of unwanted vibrations to the experimental setup. Digital temperature sensors (Maxim DS18B20) [20] were installed on the sensor plate and at a distance of 25 cm as part of the setup to record sensor and environmental temperature variations respectively ,for the entire duration of test. The setup can be seen in Figure 2.

Table 2: Key specifications ADXL-355 Digital MEMS [17]

S No	Parameter	Specification value
1	Measurement Range	± 2.048 g
2	Sensitivity	256000 LSB/g
3	Non-linearity	± 0.1 %
3	Axes	Tri-axial
4	Temperature Range	-40 to +125 °C
5	Transverse Sensitivity	≤ 1 %
6	Temperature Response	± 0.01 %/°C

The Data Acquisition Systems (DAQs) for the sensors (MEMS, IEPE and Laser) recorded individual sensor data to a PC. The DAQ of MEMS sensor was based on a Raspberry Pi 3 Model A+ and transmitted data wirelessly to the PC via the I2C protocol. Benchmarking of setup via a Laser was conducted through use of Renishaw’s propriety QuickViewXL software while data acquisition for the IEPE accelerometer was based on the National Instrument (NI) DAQ. To ensure synchronisation of timings across sensors, a shock impact event was created on the CMM bed using a hammer, the rising edge of the impact vibration acted as a trigger point for long term data recording.

In order to characterize and model the noise parameters of the low-cost MEMS sensor, the choice of installation in a vibration-isolated environment is key. Therefore, the test was conducted in a temperature-controlled environment of ±1 °C on a vibration-isolated stable granite Coordinate Measuring Machine (CMM). Moreover, to ensure a minimal effect of micro-vibrations induced in the sensor from external sources such as floor vibrations, opening and closing of doors, movement of people etc. the test was conducted over the span of a weekend.

The choice of nominal range and sampling rate for sensors is an important and critical aspect within the application of AVAR method. The nominal range of the MEMS sensor was configured as ±2 g (where g=9.81 m/s^2) to ensure a high sensitivity of operation, while the IEPE sensor was operated in its nominal operating range of ±500 g to record any high amplitude event that might not be recorded by MEMS sensor due to sensing overload. It is important to point out that MEMS sensor in its ±2 g configuration, has a very high resolution of 3.906 μg/LSB, fulfilling a key requirement of modelling underlying noise processes. A sampling rate of approximately 100 Hz. was chosen for the MEMS sensor while the IEPE sensor sampled the data at higher rate of 1650 Hz to serve as a reference for any high frequency event in the data which might appear as an outlier in MEMS data. The impact of sensor range and sampling rate on noise analysis for sensors is discussed in detail in the next section which focuses on background noise estimation using AVAR.

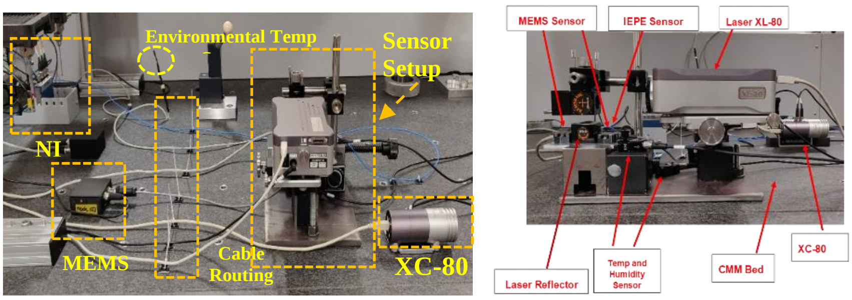

Figure 2 : Experimental Setup on CMM Bed (L) and Sensor Setup (R)

4 Results and Discussion

For an effective application of AVAR for modelling the sensor noise, measurements should be obtained in the absence of any input to the sensor, for which, the condition of 'zero excitation' was achieved by placing the sensor on a stable CMM granite bed. The vibrational stability of setup was benchmarked to

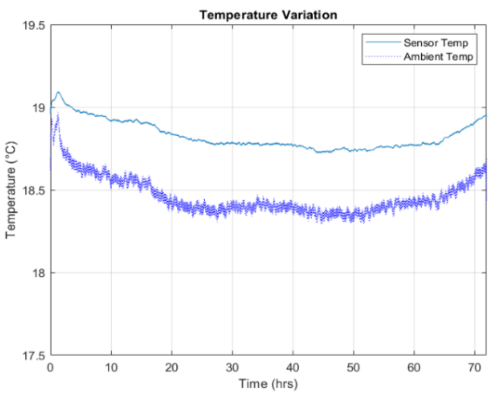

Figure 3 : Temperature variation during Test

be ±0.316µg using a laser interferometer. The sensor was placed in a temperature-controlled room to avoid effects such as environmental induced bias in the characterization of process noise, this can be seen in the plot of temperature vs time in Figure 3.
Through applying AVAR method to the whole data set, a log–log plot of the Allan Variance versus the cluster time as shown in Figure 4 for the three axes of the MEMS accelerometer, was generated in MATLAB. Through the computational analysis of the slopes of the plot according to Table 1 and Figure 1, the various noise terms that were identified are summarized in Table 3, below.

Table 3: Summary of AVAR Results for the ADXL-355

Noise Source	**X-Axis**	**Y-Axis**	**Z-Axis**	**Coefficient Units**
Quantization	-	-	-	(m/s^2)
Velocity Random Walk (VRW)	1.7121×10^{-5}	1.6685×10^{-5}	2.6592×10^{-4}	($m/s/\sqrt{s}$)
Bias Instability (BI)	3.2454×10^{-5}	2.1983×10^{-5}	7.4330×10^{-5}	(m/s^2)
Acceleration Rate Random Walk (RRW)	2.1559×10^{-5}	-	9.1834×10^{-5}	($m/s^2/\sqrt{s}$)
Rate Ramp (RR)	-	-	-	($m/s^2/s$)

It is evident from the plot that the Quantization noise does not exist in any of axes which could be attributed to the 20-bit ADC in MEMS, which provides high resolution. Similarly, the sensor seems not to be affected by RR noise as well. The results clearly indicate that VRW is the dominant error for the short cluster times (T<10 s), whereas BI is the dominant error for the long cluster times (T<10000 s).

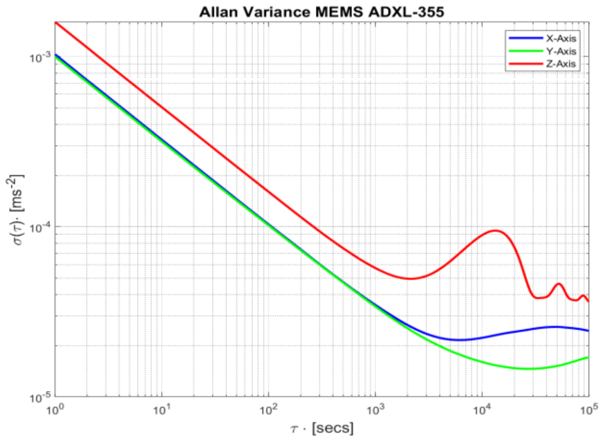

Figure 4 : Allan Variance Plot for MEMS

The X and Z axes of the MEMS seems to be affected by RRW, while the noise term is not detected in Y-axis of the sensor. Therefore, from the analysis of the results, that major noise contribution in MEMS sensor can be attributed to VRW and BI terms, in all the axis.

The estimation quality for computed results can be calculated based on the Allan Variance estimation error equation [12]. Estimation errors were found to be 0.05 % for short cluster times and 4.7 % for long cluster times. Therefore, the maximum uncertainty for computed results is in the order of 4.7 %.

5 Conclusion

The work has characterized and quantified the noise parameters of a low-cost MEMS accelerometer for use in precision manufacturing applications. The work encompassed identifying different noise terms which can affect the accuracy of vibration measurements. Through long-term stable measurements from the sensor and application of Allan Variance method, the noise characteristics of the sensor were modelled. The results obtained from AVAR can be considered satisfactory with the maximum uncertainty for analysed noise parameters computed to be at 4.7 %. The sensor is not affected by quantization noise, rate ramp or sinusoidal noise in any of the axes. While RRW was only found in the X and Z axes of sensor. The major contribution of noise for sensor in all axes is due to VRW and BI noise terms. The results from the work, offer an improved framework for sensor stability for employment of MEMS based sensor in manufacturing and industrial applications.

Based on the quantifiable information computed from AVAR, several denoising techniques such as Kalman filtering, wavelet denoising based on Discrete Wavelet transform (DWT) etc. can potentially be used to improve signal characteristics and obtain low noise floors, as well. Future work can also focus on evaluating the frequency domain noise in such MEMS sensors using techniques such as power spectral density (PSD) as it has been shown to have a strong relationship with AVAR method [11].

6 Acknowledgements

The authors gratefully acknowledge the UK’s Engineering and Physical Sciences Research Council (EPSRC) funding of the Future Metrology Hub (Grant Ref: EP/P006930/1).

References

[1] M. Galetto *et al.*, "Uncertainty evaluation in calibration of low-cost digital MEMS accelerometers for advanced manufacturing applications," *CIRP Annals*, 2019.

[2] A. Sabato *et al.*, "Wireless MEMS-Based Accelerometer Sensor Boards for Structural Vibration Monitoring: A Review," *IEEE Sensors Journal,* vol. **17, no.** 2, pp. 226-235, 2017.

[3] A. Iqbal *et al.*, "Performance evaluation of low-cost vibration sensors in precision manufacturing applications," in *20th International Conference of the European Society for Precision Engineering and Nanotechnology*, 2020, pp. 535-538: euspen.

[4] G. D’Emilia *et al.*, "Evaluation of aspects affecting measurement of three-axis accelerometers," *Measurement,* vol. **77,** pp. 95-104, 2016.

[5] K. Jerath *et al.*, "Bridging the gap between sensor noise modeling and sensor characterization," *Measurement*, vol. **116,** pp. 350-366, 2018/02/01/ 2018.

[6] P. Petkov *et al.*, "Stochastic modeling of MEMS inertial sensors," *Cybernetics and information technologies,* vol. **10, no.** 2, pp. 31-40, 2010.

[7] M. Matejček *et al.*, "New experience with Allan variance: Noise analysis of accelerometers," in *2017 Communication and Information Technologies (KIT)*, 2017, pp. 1-4.

[8] J. Jurado *et al.*, "A regression-based methodology to improve estimation of inertial sensor errors using Allan variance data," *Navigation,* vol. **66, no.** 1, pp. 251-263, 2019.

[9] F. Mohd-Yasin *et al.*, "Topical Review: Noise in MEMS," *Measurement Science & Technology - MEAS SCI TECHNOL,* vol. **21,** 01/01 2010.

[10] N. El-Sheimy *et al.*, "Analysis and modeling of inertial sensors using Allan variance," *IEEE Transactions on instrumentation and measurement,* vol. **57, no.** 1, pp. 140-149, 2007.

[11] IEEE, *IEEE STD 1293-2018 (Revision of IEEE STD 1293-1998): IEEE Standard Specification Format Guide and Test Procedure for Linear Single-Axis, Nongyroscopic Accelerometers* (IEEE STD 1293-2018). IEEE, 2019.

[12] IEEE, "IEEE STD 952-1998 : IEEE standard specification format guide and test procedure for single-axis interferometric fiber optic gyros," 1998: Institute of Electrical and Electronics Engineers New York, NY.

[13] R. Brincker *et al.*, "Obtaining and estimating low noise floors in vibration sensors," in *Proceedings of the 25th SEM International Modal Analysis Conference*, 2007.

[14] M. El-Diasty *et al.*, "Temperature variation effects on stochastic characteristics for low-cost MEMS-based inertial sensor error," *Measurement Science and Technology,* vol. **18, no.** 11, pp. 3321-3328, 2007/09/20 2007.

[15] B. ISO, "BS ISO 16063-21:2003: Methods for the calibration of vibration and shock transducers. Vibration calibration by comparison to a reference transducer," ed: British Standards Institute, 2003.

[16] B. ISO, "BS ISO 16063-11:1999: Methods for the calibration of vibration and shock transducers. Primary vibration calibration by laser interferometry," ed: British Standards Institute, 2001.

[17] A. Devices, "ADXL354/ADXL355 Low Noise, Low Drift, Low Power, 3-Axis MEMS Acceleromters Data Sheet (Rev. A)," 2018.

[18] P. Piezotronics. (2019). *PCB 356A02 Tri-axial Accelerometer Data Sheet*.

[19] Renishaw. (2019). *XL-80 Laser Measurement system*.

[20] D. S. B. P. Resolution. (2018). *DS18B20 1-Wire Digital Thermometer, Data Sheet, Maxim Integrated Products*.