# Data Quality Issues for Vibration Sensors: A Case Study in Ferrosilicon Production*


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## ABSTRACT

Digitisation in the mining and metal processing industries plays a key role in their modernisation. Production processes are more and more supported by a variety of sensors that produce large amounts of data that meant to provide insights into the performance of production infrastructures. In the metal processing industry vibration sensors are essential in the monitoring of the production infrastructure. In this position paper we present the installation of vibration sensors in a real industrial environment and discuss the data quality issues we encountered while using such sensors.



## CCS CONCEPTS

• **Information systems** → **Information systems applications**.

## KEYWORDS

vibration sensors, data quality, ferrosilicon production

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## 1 INTRODUCTION

Within mining and metal processing industries, digital transformation is becoming a driving force changing the nature of companies and interaction with employees, communities, government, and environment at every step of the value chain [1]. The metal processing industry is already gathering a huge amount of data from sensors to collect real-time information about the performance of their infrastructure. Since many processes and machines can possibly generate data, smart sensors become a primary data source

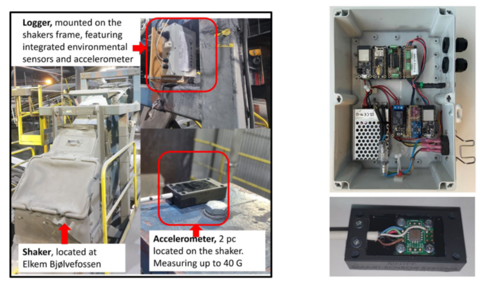


**Figure 1: Left: Vibration sensing installation in ferrosilicon crushing facility at Elkem Bjølvefossen, Norway. Right: A vibration sensor encapsulated in a 3D printed watertight package with wiring together with an overview from inside the logger enclosure that contains the ESP43 WROOM boards and the power supply unit.**

for producing insights via big data analytics. There remain however many areas where the industry lacks necessary and real-time information. Commercial sensor equipment may be available but could be too expensive or inadequate for direct implementation in the process. In addition, conditions related to the hostile nature of many processes, e.g., high temperature, dust, abrasion, corrosion, etc., may render data acquisition challenging. Research is thus needed to identify, evaluate, or develop sensor technologies to be used for real-time data gathering in harsh environments. Before smelting in metal processing, crushing, and sieving of raw materials are crucial process steps as raw materials have a large impact on the efficiency of the smelting process. Implementation of practical and reliable technologies monitoring such equipment in real-time will thus enable an improved optimisation of the smelting process. Furthermore, for the crushing and sieving process of the raw material, there is much to gain by optimising the process. Currently very little data is collected, except for the final product, which is too late to be used for process optimisation.

A case study was developed by Elkem – one of the world's leading providers of advanced material solutions – to explore vibration monitoring of mechanical sieving equipment for fault detection. The task focuses on developing suitable sensors to monitor the sieve screens in the material separators at Elkem Bjølvefossen, Norway plant with the goal to detect overfeeding and increase of the production throughput. A set of linear accelerometers were installed at selected positions on the separator and the vibration data is being collected since April 2022 (Fig. 1). Several data quality issues arise during data collection. In this position paper, we present the data acquisition pipeline and the issues that arise in the context of data


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quality assessment. In our set-up we experience data loss of 8.6% due to the chosen acquisition strategy that we will explain here in more details and propose a possible mitigation strategy.

# 2 DATA ACQUISITION PIPELINE AND DATA QUALITY ISSUES

## 2.1 Hardware Set-Up

As depicted in Fig. 1 the data acquisition is performed with the following hardware that was installed on site in the crushing and sieving facility:

- Two three-axis ADXL356 accelerometers
- ESP32 WROOM-32E
- Lenovo Thinkbook PC with Windows 10
- tp-link Archer MR 600 router

The set-up is custom made in-house and installed in a separate network to ensure full control over the acquisition pipeline. Special attention was given to design a dust and watertight encapsulation of the equipment to prevent damage during the wet cleaning of the facility and to ensure long-lasting run-time over planned evaluation period of 1 year.

## 2.2 Data Processing Pipeline

The data is transferred through FTP on WiFi to the Windows computer. A telegraf service is running on the Windows machine constantly sending newly arrived accelerometer data to an influxDB instance that is deployed in the cloud. Fig. 2 shows a high-level architecture of the logging pipeline from the sensors to the cloud. The data is sampled during an acquisition window of 3 minutes at 1 kHz before it is sent to the Windows PC during a 17 seconds sampling pause for further handling (Fig. 3). Fig. 3 shows also the accelerometer signal at 3 axes as it is being acquired by the analogue digital converters (ADC) of the ESP32 WROOM board. We see that there are two dominant axes (adc0 and adc2) the third axis seems to pick up just noise. Similar data characteristics apply to the second vibration sensor. In addition to vibration data, manufacturing execution system (MES) data, as well as, other process data as product packaging speed is being collected in the same influxDB.

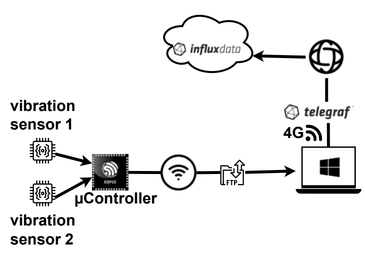


**Figure 2: Overview of the data sampling pipeline from the vibration sensor into a time series data base in the cloud.**

The process data allows for precise interpretation of the vibration data and is used for labelling in the later evaluation step. Here, we use python scripts to identify and prototype a suitable analytics and prediction framework with a goal to deploy it on site at the factory.

## 2.3 Data Quality Issues

The main data quality issue is related to data loss due to communication overhead and malfunction of the hardware. The microcontroller sampling routine as well as the process to send the data over FTP to the Windows server runs as a single thread. While the data is being sent to permanent storage, no data acquisition can take place in the current set-up. The duty cycle hence consists of 3 minutes data acquisition followed by a 17 seconds of data transfer as seen in Fig. 3, resulting in an 8.6% data loss per acquisition cycle. This strategy is sub-optimal in the current research setting where we are aiming to detect events on a sub-second scale. Further we experienced data loss of 1 month from one of the sensors due to cable wear from the mechanical abrasion of the connecting sensor cable.

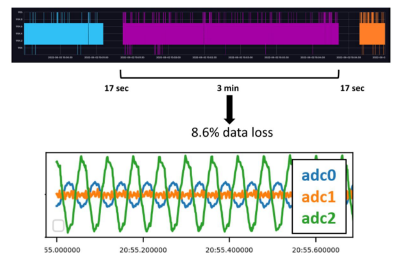


**Figure 3: Top: Vibration data from a single accelerometer sampled at 1 kHz with acquisition gaps. Bottom: Vibration data from a single sensor consisting of 3 measurements at orthogonal axes.**

# 3 SUMMARY AND OUTLOOK

We presented the acquisition pipeline consisting of the instrumentation set-up and software logging routines to be capable of collecting vibration data that is sampled at 1 kHz. The gaps in the data acquisition can be avoided by either making use of the multi-threading capabilities of the microcontroller or reducing the sampling rate such that the acquired data can be sent in very small chunks to minimise the communication overhead. The sieving unit vibrates with a frequency of 16 Hz, and we assume that the information that is relevant for the task of performance optimisation of the crushing facility is in the range of few hundred Hz therefore posing a lower requirement towards the sampling frequency. The experimental data acquisition set-up is meant to collect vibration data for one year. Once the data collection is finalised, we aim at building an analytics pipeline that allows us to correlate process data from the manufacturing execution system (MES) to optimise for key performance indicators downstream as for example the packing speed of the ferrosilicon in bags to be shipped to the customer. Further, we aim at being able to tackle questions regarding predictive maintenance of the facility by analysing extraordinary events detected through the vibration measurements of the sieving unit.

# REFERENCES

[1] World Economic Forum. 2017. Digital Transformation Initiative, Mining and Metals Industry. In *White paper*.