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APPLIED RESEARCH

Vibration Sensors for Detecting Critical Events: A Case Study in Ferrosilicon Production

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ABSTRACT The mining and metal processing industries are undergoing a transformation through digitization, with sensors and data analysis playing a crucial role in modernization and increased efficiency. Vibration sensors are particularly important in monitoring production infrastructure in metal processing plants. This paper presents the installation of vibration sensors in an actual industrial environment and the results of spectral vibration data analysis. The study demonstrates that vibration sensors can be installed in challenging environments such as metal processing plants and that analyzing vibration patterns can provide valuable insights into predicting machine failures and different machine states. By utilizing dimensionality reduction and dominant frequency observation, we analyzed vibration data and identified patterns that are indicative of potential machine states and critical events that reduce production throughput. This information can be used to improve maintenance, minimize downtime, and ultimately enhance the production process's overall efficiency. This study highlights the importance of digitization and data analysis in the mining and metal processing industries, particularly the capability not only to predict critical events before they impact production throughput and take action accordingly but also to identify machine states for legacy equipment and be part of retrofitting strategies.

INDEX TERMS Data management, data mining, classification, ferrosilicon production, sensor data, time series, vibration sensors.

I. 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 the environment at every step of the value chain [1], [2], [3]. 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 [4], [5]. Since many processes and machines can possibly generate data, smart sensors–instruments with on-board signal conditioning or feature extraction capabilities–become a primary data source for producing insights via big data analytics [6], [7]. 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 [8]. Research is thus needed to identify, evaluate, or develop sensor technologies (both at the hardware and software levels) to be used for real-time data gathering in harsh environments. To investigate the use of sensor technologies in this context, a case study was developed by Elkem[1]–one of the world's

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[1]https://www.elkem.com, accessed on March 13, 2023

leading providers of advanced material solutions–exploring vibration monitoring of mechanical sieving equipment for fault detection and process optimization. The task focused on deploying suitable sensors to monitor the material separators at Elkem Bjølvefossen plant in Norway, with the goal to detect unforeseen events and eventually increase the production throughput. Prior investigations using off-the-shelf IoT sensors had been unsuccessful in characterizing and detecting faulty behavior at this plant. It was concluded that commercial IoT solutions were not appropriate for the task. Such sensors are almost always battery-powered, leading to low data rates, short maintenance intervals, or both. Early fault signatures are much weaker than the ordinary shaking behavior and must be extracted through complex feature engineering based on large datasets [9], [10]. A custom, high-performance solution was thus developed to supply a set of 1000 samples per second continuous wave-forms, from which a wide landscape of feature extraction techniques could be explored. We proposed a full stack pipeline from sensor installation to data collection, management, and analytics to reach the above-mentioned goal.

The use of vibration sensors for machine condition monitoring has been rigorously used in various industries and has also been presented in the scientific literature (e.g., [11], [12], [13], [14]), however, without deployment and large scale validation of the proposed methodologies in industrial settings. The lack of studies in an industrial setting is also reported in a review of more than 100 articles in [15]. It was shown in [16] that vibration data can detect quality faults in additive manufacturing or detect wear of rotatory elements of a paper mill machine [17]. In [18], the monitoring process of the vibrations (as recorded by accelerometers) was successfully applied for tool wear estimation, and in [19], the authors presented a method to track the operational status of legacy manufacturing systems using vibration data. In [20], it was successfully demonstrated that vibration measurements can be used to detect structural damages in concrete structures. Such previous results indicate that the installation of vibration sensors and continuous evaluation of vibration patterns can also bring value to the manufacturing processes in ferrosilicon production, which we aimed to investigate with the work presented in this paper.

To start with, a set of 3-axis micro-electromechanical systems (MEMS) accelerometers were successfully installed at selected positions on a material separator at the Elkem Bjølvefossen plant. Capacitive and piezoelectric sensors offer excellent performance for condition monitoring, but they can be costly. As a result, there is increasing interest in replacing such conventional sensors with MEMS-based sensors for this kind of application, which was also our motivation to choose this technology. The collected data was analyzed with a set of unsupervised methods to project the vibration measurements into latent feature spaces to quantitatively compare and develop visual intuitions about abnormal and unwanted behavior of the separator in the production process. In addition, by performing a logistic regression, we could show that the vibration data could be potentially used to train a statistical model to predict various performance indicators and machine states within the factory. Specifically, we were able to identify different modes of operation of the separator and two critical failure events just by observing the dominant frequency of the oscillations. Hence, we postulate that a statistical model can be used to identify and possibly predict the behavior of the separator to provide insight into the ferrosilicon production process.

While the principal focus of this paper does not revolve around the introduction of novel hardware or software methodologies, it does serve as a demonstrative case study illustrating the feasibility of employing cost-effective vibration sensing and data analytics within a wide-scale deployment. Furthermore, the paper reports on the diverse challenges that necessitated resolution throughout the course of this endeavor.

The main contributions of this work include: (1) development of a low-cost, high-performance vibration sensing solution; (2) installation of the sensing framework in a real industrial setting in a harsh environment; (3) collection and management of high-density vibration data; (4) statistical analysis of collected data which showed its potential to detect critical events and identify patterns related to machine states but without prospective validation due to changes in the production after data collection; (5) a labeled data set is made publicly available.

The remainder of this paper is organized as follows. Section II describes the sensor development and installation, and the data acquisition and processing pipelines. Section III describes the results of data processing and analysis, and what patterns were identified. Section IV discusses the results of this case study and data analysis, and Section V summarizes this paper and outlines potential for future work.

II. SENSOR DEVELOPMENT, INSTALLATION, DATA ACQUISITION, AND PROCESSING

In this section, we present details on the production process and the installation of the sensors (Section II-A), the design of the sensors (Section II-B), and the data acquisition pipeline (Section II-C). The hardware set-up and the data acquisition pipeline were briefly introduced in [21] in the context of data quality. Section II-D provides an overview of the collected data, and in Section II-E, we describe how the collected data was processed for the statistical analysis. This section can be regarded as the description of the materials and methods used for the experiment.

A. FERROSILICON PRODUCTION PROCESS AND SENSOR INSTALLATION

The Elkem Bjølvefossen facility specializes in producing ferrosilicon (FeSi) and ferrosilicon magnesium (FSM) master alloys. Elkem Bjølvefossen is among the world's largest producers of FSM. Three reduction furnaces deliver the base metal, which is then alloyed and refined to the right quality of FeSi or FSM. These alloys are important additives in the

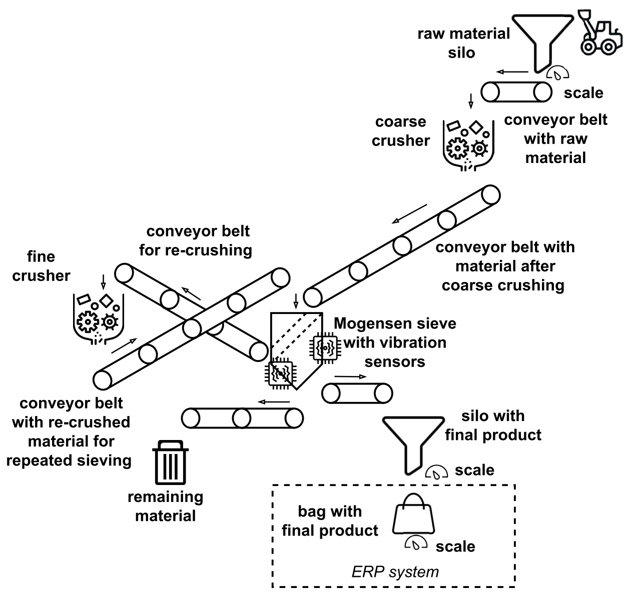

FIGURE 1. Depiction of the crushing and sieving process of Elkem's FeSi production in Bjølvefossen. Arrows show the direction of conveyor movement. The packing speed is derived from the scale where the packed bags with the final product are weighed, and the information is stored in the ERP system.

manufacturing of steel products. Silicon in the form of FeSi is used to remove oxygen from the steel and as an alloying element to improve the final quality of the steel. Silicon increases strength and wear resistance, elasticity (i.e., spring steels), scale resistance, and heat-resistant steels and lowers electrical conductivity and magnetostriction.

After tapping and refining, the ferro-alloys are crushed to grains ranging from 1 mm to 25 mm in size. Consumers of FeSi and FSM have strict requirements for particle size, related mainly to the chemical kinetics of their refining and alloying processes. For this reason, the crushed material is separated in sieves and packaged by particle size before shipment. Two lattice gratings inside the Mogensen shaker separate the material according to the required particle size. The crushing and sieving process is depicted in Figure 1. The raw material is crushed once before first sieving. Oversized material is transported to a second crusher for refinement before being sieved again. The final material is packed in bags for shipping. There are several scales located at the silos that measure the current weight of material inside this silo.

The subject of the present study is a mechanical shaker platform containing one or more such sieves. The shaker is a Mogensen S0556[2] that was installed in 1996 in Bjølvefossen and is no longer produced in this type. This device is powered by two counter-rotating 1.2-horsepower AC motors operating at 960 RPM. Together with the spring suspension, these cause an elliptical motion that both transports and scatters the incoming material across the sieve. The shaker is engineered so that the motion transitions from a slanted ellipse at the in-feed to nearly linear at the output. It is, therefore, of diagnostic interest to deploy multi-axis accelerometers at multiple locations.

Figure 2 depicts the Mogensen separator, the placement of the logger, and one of the two vibration sensors. The first sensor was mounted on the suspension block near the outlet chute, where motion is purely vertical; this was confirmed by checking the relative vibration magnitude in the x-y-z directions. The second sensor was mounted on the service door flange right above the motors and angled to the principal axes of the elliptical motion. These locations were chosen to cover a wide range of motion directions of the separator. The data logger was installed nearby on a stationary platform.

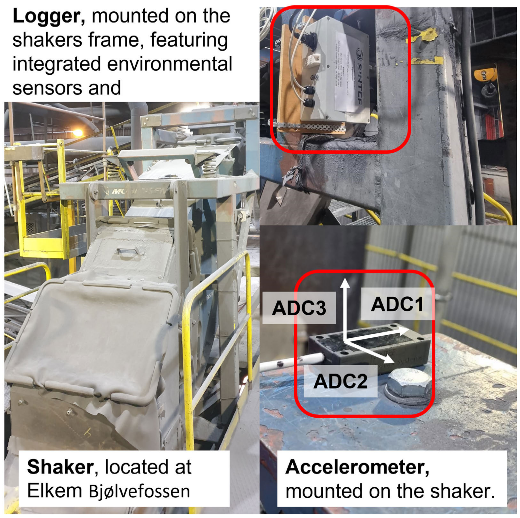

FIGURE 2. Vibration sensing installation in ferrosilicon crushing facility at Elkem Bjølvefossen, Norway, on the Mogensen shaker. One sensor is shown in the photo, whereas two have been installed on the shaker.

B. HARDWARE SET-UP OF THE VIBRATION SENSORS

As depicted in Figure 3, the data acquisition was performed with the following hardware installed on-site in the crushing and sieving facility:

- Two purpose-built three-axis vibration sensors.
- A custom-made data logger unit to sample and collect the data.
- Lenovo Thinkbook PC with Windows 10 to send the data to the cloud and to act as a remote access point.
- TP-Link Archer MR 600 4G LTE router to provide a link to the Internet.

The vibration sensors use ADXL356C accelerometers from Analog Devices.[3] These include a 300 Hz low-pass filter for analog conditioning. The sensors were validated on a vibration test bench. Since the experiment is trend-based and not reliant on absolute measurements, resources and effort were not spent on obtaining certified calibrations.

The data logger unit comprises an MCP3208 8-channel analog-digital converter (ADC) and an ESP32

[2]https://www.mogensen.se, accessed on March 13, 2023

[3]https://www.analog.com, accessed on March 13, 2023

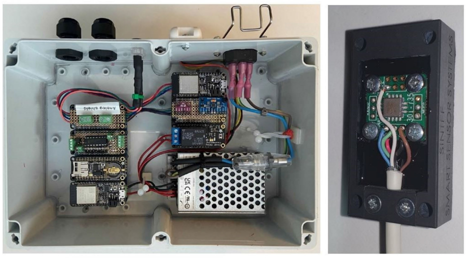

FIGURE 3. A vibration sensor encapsulated in a 3D printed watertight package with wiring (right) together with an overview from inside the logger enclosure that contains the ESP32 WROOM boards and the power supply unit (left).

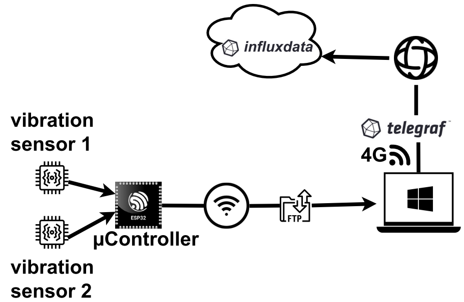

FIGURE 4. Overview of the data sampling pipeline from the vibration sensor into a time series database in the cloud.

WROOM-32E[4] for data acquisition, a 32GB SD-card for local data storage as a fallback in case of unexpected transmission failures, a second ESP32 WROOM-32E serving as an up-time watchdog to monitor the logger activity, and a 230VAC-to-12VDC power supply.

The set-up is custom made in-house and installed in a separate network at the plant to ensure full control over the acquisition pipeline. To avoid aliasing, data was sampled at 1 kHz per channel, which is more than 3 times the bandwidth of the sensor. We study up to 10 harmonics of the 16 Hz shaker action, leaving enough bandwidth for apodization and digital pre-filtering.

Since the data logger was purpose-built and aspects of the environment were unknown, conservative design choices were made with respect to the sampling strategy and resulted in non-uniform sampling coverage as described later in the paper. Attention was given to designing a dust and watertight encapsulation of the equipment to prevent damage during wet cleaning of the facility and to ensure functional longevity in the very dusty crushing-and-sieving environment. Due to the presence of large AC motors that drive the separators, attention was given to electromagnetic shielding of cables and ground loop avoidance. Stability and quality of 4G reception inside the premises were not known beforehand, nor the quality of Wi-Fi coverage. Therefore, the system had to be built to log even without access to Wi-Fi or the Internet. The logger could continue to save data to the SD-card for several weeks without the need to access a physical network. Finally, to ensure software stability, multi-threading was eschewed in favor of an alternating pattern of logging and uploading data.

C. DATA ACQUISITION PIPELINE

The data is transferred through FTP on WiFi to the Windows computer, which was placed near the logger at the Mogensen separator. A Telegraf[5] service was running on the Windows machine, constantly sending newly arrived accelerometer data to an InfluxDB[6] instance deployed in the cloud. Figure 4 depicts a high-level architecture of the logging pipeline from the sensors to the cloud. Data is sampled during an acquisition window of three minutes at 1 kHz before it is sent to the Windows PC during a 17-second sampling pause for further handling, as depicted in Figure 5. The figure also shows the 3-axis acceleration signal of the first sensor as it is being acquired by the ADCs of the ESP32 WROOM board. As expected, the motion is linear sinusoidal and aligned nearly along the z-axis (ADC3, ADC7) with some forward-axis motion (ADC1, ADC5). The labels ADC4 and ADC8 are used for the reference voltage and are not relevant for our analysis. There is lower amplitude side-to-side motion (ADC2, ADC6), as expected. Data from the second sensor is qualitatively similar.

TABLE 1. Overview of the vibration data and reasons for data loss.

Time Period	Data Description
April 7	Sensors were installed during the downtime of the facility.
April 7 – May 9	Sampling duty cycle is 999 sec/230 sec, resulting in an overall data loss of ∼23%, and mean consecutive data sampling window of 943.36 seconds.
April 30 – May 26	Data deterioration and even complete drop-outs due to cable wear from the mechanical abrasion of the connecting sensor cable.
May 26 – June 15	Vibration data available only for a single sensor (ADC1-ADC3) due to a broken cable.
May 26 – September 8	Sampling duty cycle is 179 sec/17 sec, resulting in an overall data loss of ∼9%, and mean consecutive data sampling window of 178.94 seconds.
June 14 - June 15	Data logger turned off to fix the broken accelerometer cable.
August 5 – August 8	Production stop due to faulty motor installation on one of the conveyor belts on August 4 and subsequent downtime of the facility to fix the issue. The vibration sensor went back into operation on August 8, although the Mogensen unit was already operational on August 5.
August 16 – August 19	Downtime of the facility for cleaning.
September 8	End of the experiment due to decommissioning and removal of the Mogensen separator.

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 setup. Two sampling strategies have been configured for different

[4]https://www.espressif.com/en/products/modules/esp32, accessed on March 13, 2023
[5]https://www.influxdata.com/time-series-platform/telegraf, accessed on March 13, 2023
[6]https://www.influxdata.com/get-influxdb, accessed on March 13, 2023

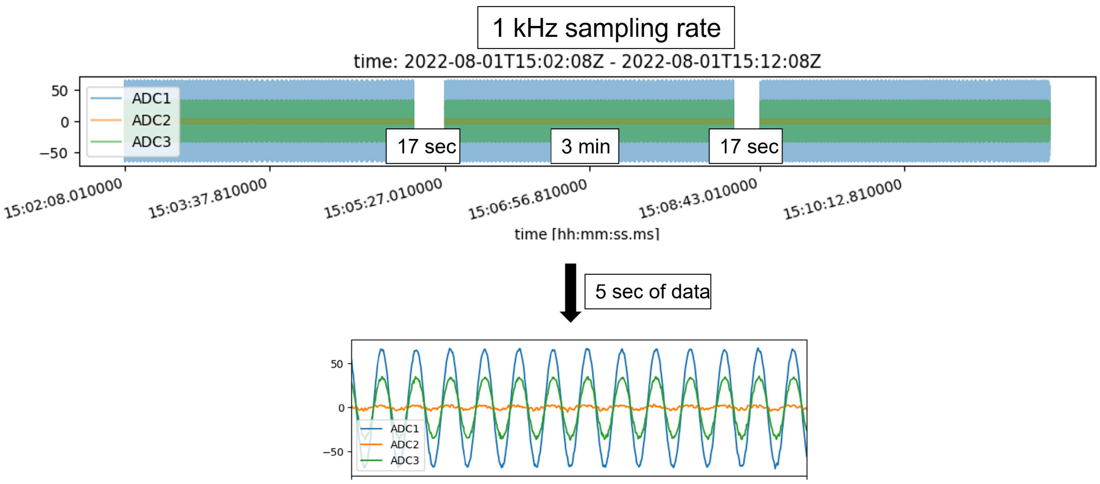

FIGURE 5. Top: Vibration data from a single accelerometer sampled at 1 kHz for 3 minutes with acquisition gaps of 17 seconds. Bottom: Vibration data for five seconds from a single sensor consisting of three measurements at orthogonal axes.

time periods, as described in Table 1, providing a detailed overview of the data acquisition settings and the reasons for data loss during specific periods. One measurement cycle consisted of three minutes of data acquisition followed by an acquisition pause of 17 seconds for data transfer, as seen in Figure 5, resulting in an 8.6% data loss per acquisition cycle. The different acquisition timings resulted from adjustments to the sampling strategy during the measurement campaign to reduce data loss.

D. DATA INVENTORY

1) VIBRATION DATA

We acquired vibration data from the two sensors. Each sensor measures acceleration in three axes with three different ADCs. Due to various reasons such as power outage, planned facility downtime, and cable wear, the collected data is not contiguous over the whole time of the experiment (Figure 6). In addition, the sampling was not continuous due to the need for transferring data from the SD-card to the FTP-server (by design). The resulting sampling pattern for signal acquisition is described in Table 1 together with other reasons for data loss.

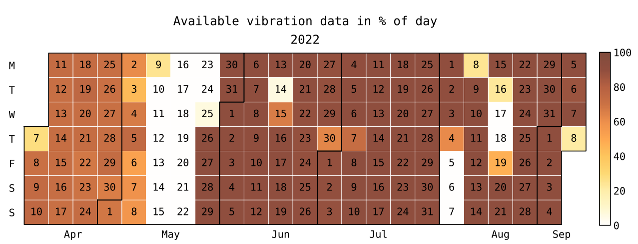

FIGURE 6. Data that was acquired in % of a day for the period of the experiment.

2) PROCESS DATA

In addition to the vibration data, we collected Manufacturing Execution System (MES) data, as well as process data from the Enterprise Resource Planning (ERP) database, providing information about the material currently being packed and data from the scales at the material packing station where the bags with completed production were packed. MES data has a resolution of 5 seconds, and the process data from ERP has a resolution of roughly 10 minutes. This operational data is meant to provide insight into the current state and throughput of the facility and will serve as labels for the correlation analysis with the vibration data.

Another important performance indicator is *overfeeding*. It occurs when the separator lattice gratings are clogged, and material can no longer be sieved. This happens regularly and is only reflected by the decrease in the sieving speed and subsequently the packing speed, which can be detected by an experienced process engineer. To address this issue, the separator is stopped periodically for manual cleaning of the sieve. Although undesirable, no concrete data exist that mark when overfeeding happens and what its influence is on the downstream packing speed, which is reflected by the ERP data.

3) EVENTS REPORTED BY PROCESS ENGINEERS

Furthermore, two unforeseen events were reported by the process engineers of the facility that led to unwanted production stops. The first event happened on May 3 due to a motor failure on the Mogensen shaker. The second event occurred on August 4, leading to a complete production stoppage, where the reason was a fault on one of the conveyor belts. The conveyor belt was moving in the wrong direction, transporting the material to the separator instead of away from it. This led to a long downtime of the facility to fix the issue, clean the separator, and tidy up the facility. These issues could have been prevented if an effective detection of failures had been in place.

E. DATA PROCESSING

1) PREPARATION OF THE FACILITY'S MES AND ERP DATA

To extract the data points from the MES data that reflect the sieving speed, we performed outlier detection on the first temporal derivative of the data, rejecting 20% of data points with Isolation Forest [22]. This outlier rejection was necessary as the scale is sometimes perturbed by the operator when handling the bag, resulting in inconsistent, rapidly changing measurements. After outlier rejection, the weight measurements were replaced through linear interpolation.

Additionally, on April 17 and July 27-28, a discrepancy was observed between sieving speed (MES) and packing speed (ERP) due to label mismatch. The bags were wrongly labeled as coming from a different separator, leading to the appearance of no packed material for those days. These days were excluded from our analysis.

2) PRE-PROCESSING OF VIBRATION DATA WITH FOURIER TRANSFORM FOR SPECTRAL ANALYSIS

The available vibration data were transformed to the frequency domain through a Fourier transform on a window size of 1 minute to observe potential changes in dominant frequencies. Here, we used the Python library *SciPy*.

To develop intuitions on how the vibration patterns and frequencies are related not only to the machine states and failures of the Mogensen separator but also to possible throughput characteristics in the overall production process, we performed common statistical evaluations such as dimensionality reduction and clustering, and a simple regression. We assumed that analyzing the frequencies would allow us to better interpret and understand the data. Moreover, it allowed us to reduce the amount of data by twofold from 60,000 to 30,000 samples per minute. We further reduced the data load in two different ways: one where we sub-sampled the full frequency spectrum of 0-500 Hz from 30,000 to 1,000 points per minute and per accelerometer, and the other where we took the full spectral resolution but observed only the frequencies ≤ 25 Hz, resulting in 1,500 points per minute and per accelerometer. In this fashion, we processed every day of the available vibration data for each of the three channels of the two vibration sensors.

Furthermore, we performed a correlation analysis between the vibration sensors and their axes, regarding them as six different channels. Already from the raw accelerometer signals that essentially resemble a sinusoidal, we postulated that all six channels are heavily correlated. Under this assumption, we investigated whether all channels are needed to represent the information. We calculated the Pearson correlation coefficient (PCC) on the mean power spectrum. Further, we performed a simple principal component analysis (PCA) to see if we could transform the multivariate signal from six channels into fewer. Here, we used the Python library *seaborn*.

3) DIMENSIONALITY REDUCTION OF SPECTRAL VIBRATION DATA

For the dimensionality reduction, the features are represented by the frequencies detected by the two vibration sensors for every minute when the Mogensen unit was operational. Due to different sampling strategies and signal drops for one of the vibration sensors, we divided the data into three parts as shown in Table 2 to calculate and analyze the clusters that form after dimensionality reduction to two dimensions on all 6,000 features in time.

TABLE 2. Partitions of the vibration data due to different characteristics of the sampling and data availability.

Time Period	Data Description
Part 1: April 7 – May 9	Analyses the data from the 17 minutes consecutive sampling periods.
Part 2: May 25 – June 15	Analyses the data from the 3 minutes consecutive sampling periods. Here, we miss data from one of the vibration sensors due to a broken cable. Therefore, only data from 3 accelerometers is available.
Part 3: June 15 on-wards	Analyses the data from the 3 minutes consecutive sampling periods and corresponds.

To understand whether we can detect clustering and outliers in the vibration data, we applied common dimensionality reduction methods such as PCA, multidimensional scaling (MDS), t-distributed stochastic neighbor embedding (t-SNE), and uniform manifold approximation and projection (UMAP) to the extracted frequency spectra and qualitatively evaluated the clusters that formed in the first two dimensions by color-coding them with the labels of interest, such as particle size, packing speed, or operational status of the sieve. Here, we used the Python libraries *scikit-learn* and *umap*. It was suggested that UMAP performed best on spectral frequency data, as shown in [23] and [24], where the authors showed that UMAP+HDBSCAN provides the best results on time series and spectrogram dimensionality reduction and classification. Figure 7 shows a summary of the collected data that is used for clustering and correlation analysis.

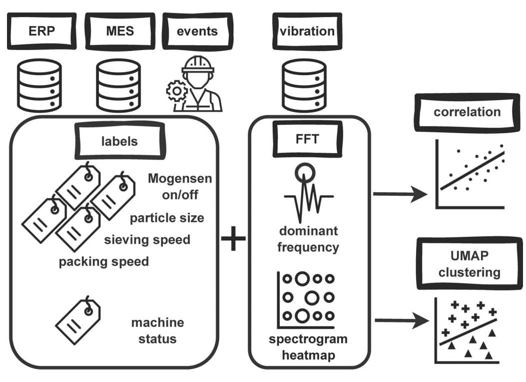

FIGURE 7. Depiction of the data processing pipeline. Labels are extracted from the MES and ERP data in addition to reported events by process engineers to analyze and explain variability in the collected vibration data through correlation of the dominant frequency and dimensionality reduction in frequency domain after a Fast Fourier Transform (FFT).

We performed a Multinomial Logistic Regression analysis to show that the spectra of the vibration data carry information about the labels as extracted from the MES and ERP data using the Python library *scikit-learn*.

III. RESULTS

In this section, we present how the collected data was utilized to show to what extent the process data and the collected vibration data are correlated. We were particularly interested in the production throughput as a performance indicator, as well as in unplanned production stops due to critical events that influence it. The aim was to understand the predictive capabilities of the vibration data towards the production throughput and its indicators.

First, we identified the labels that, according to Bjølvefossen's process engineers, are relevant for production performance after preprocessing (Section III-A). Once the relevant labels are extracted, we present the results of processed vibration data after converting it to the frequency domain to understand the signal composition and its relation to process data (Section III-B).

A. INTERPRETATION OF THE FACILITY'S MES AND ERP DATA

MES data and ERP data provide information about the current state of the operation as well production capacity of the facility. We analyzed these data to extract labels that are relevant for correlation with the vibration data. The value of the silo scale before the packing station is of interest as it directly shows the speed at which the material is arriving after the sieving process, therefore showing the sieving speed of the process. The data, however, shows also when the silo was emptied for bag filling, which does not allow for a direct conclusion on the sieving speed but still can serve as an indicator.

Also, from the MES data, we can extract when the Mogensen separator was in operation. Here, we could calculate how much time the separator was active as a percentage of a 24-hour period for every day of the experiment. This is depicted in Figure 8, where we can see that the unit was not in continuous operation. This is due to the use of other separators for different processes or downtime or scheduled cleaning on all Thursdays. Here, we are interested in unintended downtimes or other process interruptions due to faults in the process where the Mogensen separator was in use and that affected the packing speed. This we can deduce from the provided ERP data from the inventory system, where it is possible to calculate how the weight of the currently packed bag of ferrosilicon particles is changing.

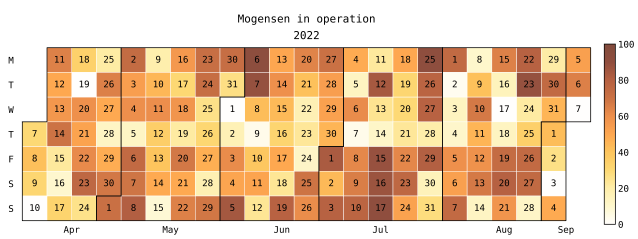

FIGURE 8. Times of operations for the Mogensen separator in % of the day as extracted from the MES data for each day of the experiment period. The black line separates the months of the year (April 7 - September 7).

We evaluated the histogram of the packing speed for each of the particle sizes individually to see if the peak of the histogram has a different location. Here, we observed different packing speed for different particle sizes, as can be seen in the histogram density plot and in the box plot in Figure 9. Therefore, the particle size needs to be taken into account when analyzing the vibration data. We also see that the most common size that is being produced is 3-25mm with 4441 bags followed by 4-25mm with 1212 bags. Further, we looked into the temporal aspect of packing speed as well as particle size to see whether there is a dependency.

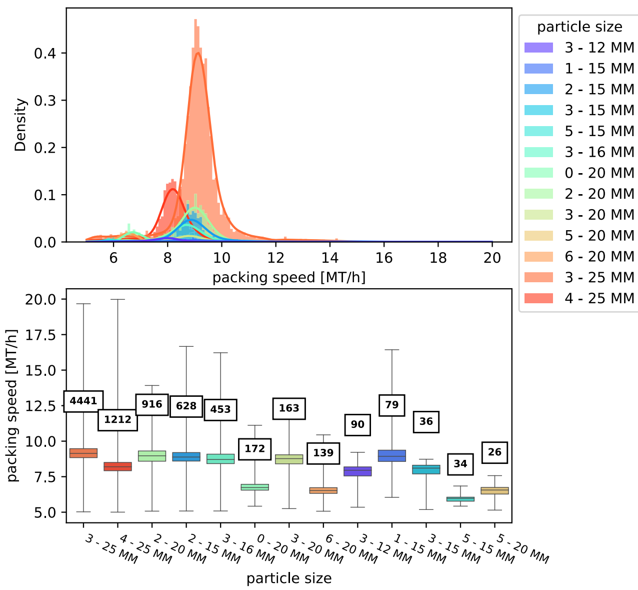

FIGURE 9. Top: Normalized probability density plot of the packing speed in metric tons per hour for different particle sizes. Bottom: Boxplot for packing speed sorted by the number of measurements during the period of the experiment, which are also indicated by a label over each box.

We can say that there is no dependency on the time of the day on the median packing speed for all collected data that stays stable at a median of 9 tons per hour (t/h) if aggregated for all particle sizes. Also, we do not observe any preference for packing certain particle sizes at the time of the day. However, there are some days during the time of data collection where there is very low packing speed reported, even though the Mogensen unit was operational.

B. DIMENSIONALITY REDUCTION AND CLUSTERING OF VIBRATION SPECTRA

Figure 10 shows the frequency spectrum for frequencies for a single typical day on April 13 together with some operational data. Here, we clearly see the dominant frequency at 16.5 Hz at which the Mogensen separator is vibrating together with the corresponding packing speed for three different particle sizes.

Again for April 13, Figure 11 shows that to explain 98% of the signal variance, we need already four components and that not all channels are correlated based on Pearson's coefficient. However, we need to investigate further why

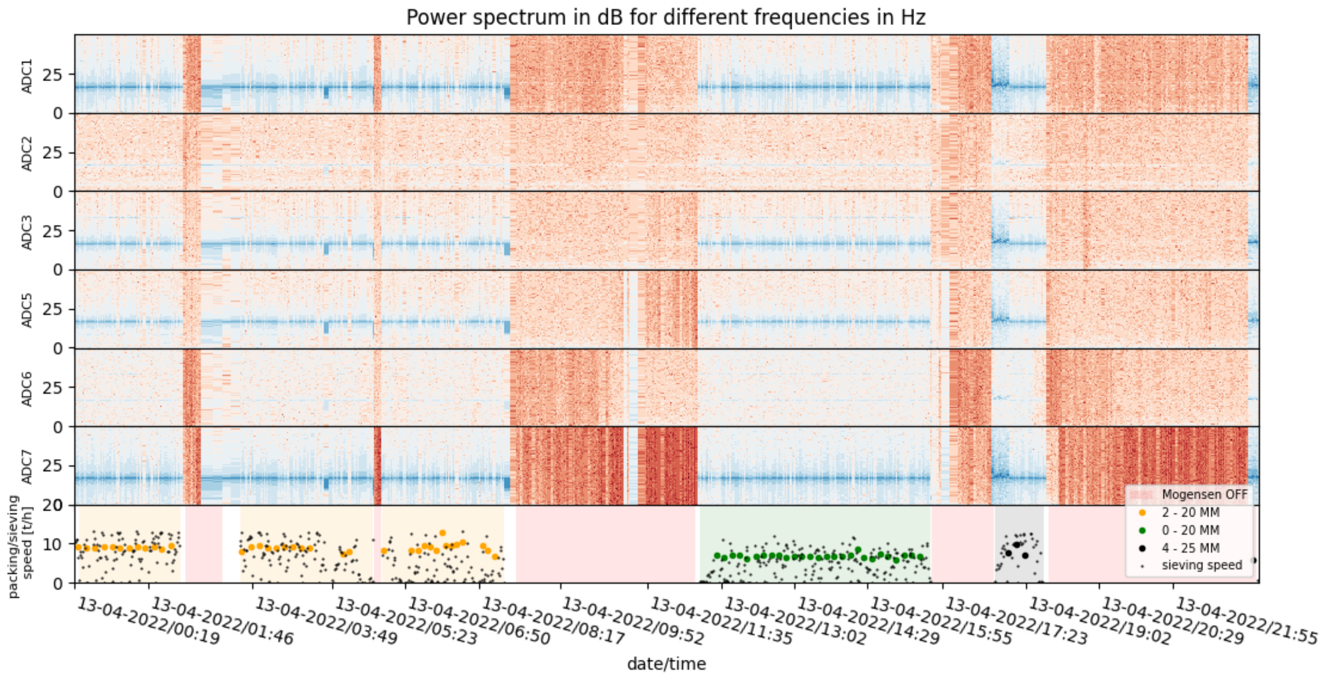

FIGURE 10. **Spectrogram for April 13 together with packing and sieving speed for different sizes and colored in red periods when the Mogensen separator was not operational. The color code for the spectrogram is red to blue for low and high amplitudes of the frequencies, respectively. Frequencies up to 50 Hz are shown to see the vibration at 16.5 Hz for the dominant frequency of the Mogensen separator.**

signals from ADC 1, 3, 5, 7 are correlated in contrast to ADC 2 and 6. For that, we analyzed the spectra when the Mogensen separator was inactive to see the background vibration that may be caused by nearby machinery. We could see that the background vibration signal is heavily correlated in all accelerometers with a PCC between 0.70 - 0.93 and 87% of variance being explained by the first component. This gave us reason to believe that the correlation between the accelerometers is partially caused by this effect. Hence, we refrained from channel fusion or transformation and rather have taken all six accelerometer signals into account during further analysis.

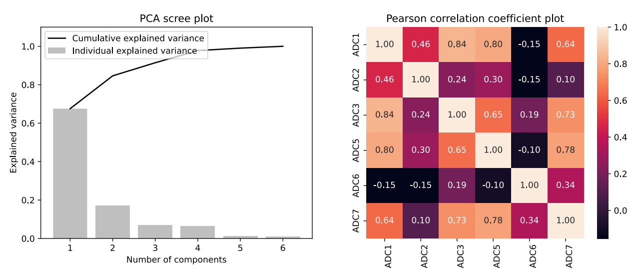

FIGURE 11. **Left: Scree plot after a PCA with cumulative and individual explained variance. Right: Pearson's correlation coefficient for the mean vibration power spectrum for data from April 13.**

1) PACKING SPEED

Further, we analyze the vibration data only within the cohort of the same particle size that is being sieved since we see prominent clustering by particle size as shown in Figure 12. Qualitatively, we observed that UMAP produces smaller and denser clusters that are far apart compared to clusters forming after PCA, MDS, and t-SNE dimensionality reduction. We do not see any direct correlation with packing speed. Here, further investigation is needed to possibly be able to find dependencies between the vibration patterns and production throughput measured by packing speed. We also wanted to see whether the dominant vibration frequency of the sieve at ca. 16.5 Hz is influenced by the particle size being sieved and if we can possibly detect when the Mogensen unit is under load with material or empty or even overfeeding.

2) PARTICLE SIZE

We did not see any significant changes in the dominant frequency, which remained stable at a median of 16.55 Hz for all accelerometers independent of the particle size being sieved. The median amplitude of the dominant frequency also did not change depending on the chosen grating for sieving in any of the accelerometers. This means that the patterns that were identified in the data after UMAP dimensionality reduction are not caused by the dominant frequency but rather in higher frequency spectra, which are more subtle and therefore carry important information. We were able to train a Multinomial Logistic Regression model with a 25% test split to predict the sieved particle size based on the frequency spectra from the 2 accelerometers with good results. Here, we report the results for part 1: average accuracy 0.93,

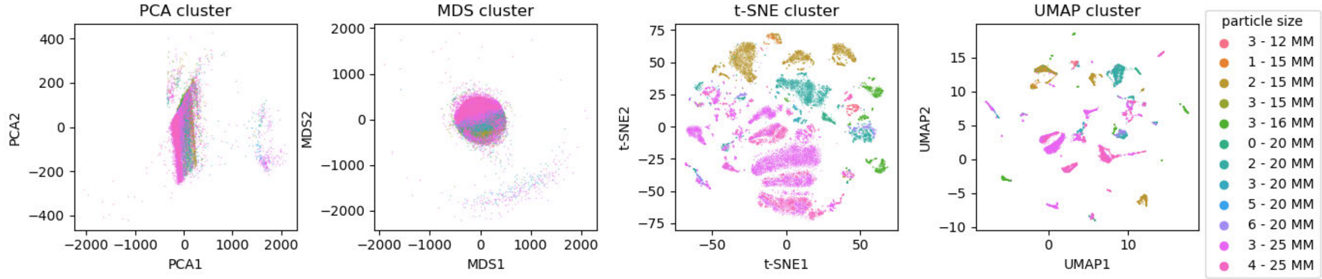

FIGURE 12. The first 2 components from the dimensionality reduction colored by the respective particle sizes that are being processed for Part 1 which is from April 7 - May 9. It is evident that UMAP produces denser and smaller clusters compared to the other evaluated dimensionality reduction methods.

precision 0.92, recall 0.89, and f1-score 0.90. Similar results were obtained for parts 2 and 3.

3) SEPARATOR UNDER LOAD OR EMPTY

To detect when the sieve is empty or under load, we take the sieving speed as an indicator. Especially in the beginning of each sieving round with a new particle size, the silos and the conveyor belts are emptied to ensure a single size in the packed bag. During the emptying process, the separator runs without material which is also reflected by reduced sieving speed. We intend to find out if we can see any clustering after dimensionality reduction when looking at the data for a single particle size of 3 – 25 mm from the part three time period from June 15 onward. Here, we see clear clusters that correlate with the sieving speed as shown in Figure 13. If we again just look at the dominant frequency we don't see any changes neither in the frequency nor in the amplitude of the peak. Hence, we assume that the clusters are caused by other spectra than the dominant one.

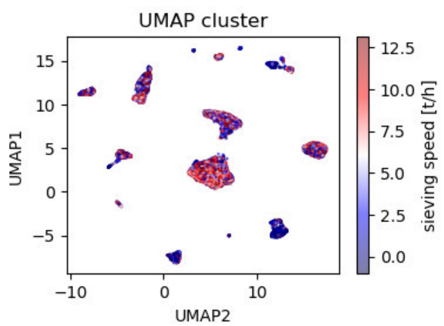

FIGURE 13. The first two dimensions of the UMAP showing different clusters that are partially explained by the sieving speed. Data from part 3 for particle size 3 - 25 mm.

4) REPORTED EVENT OF MOTOR FAILURE

On May 3^{rd}, the site engineer reported a major failure on the Mogensen unit where one of the motors failed which resulted in unintended downtime of several hours. When observing the power spectra for this period, we see that already from the beginning of Mogensen operation after service, the vibration pattern changed as seen in the clustering depending on the status of the machine as shown in Figure 14. Following this finding, we reduced the analysis to the dominant frequency at 16 Hz where we also observe a significant drop (Mann-Whitney-Wilcoxon test, $p \leq 10^{-4}$) in the mean vibration frequency in all accelerometers from 16.57 Hz to 16.49 Hz. Further, we saw a significant change (Mann-Whitney-Wilcoxon test, $p \leq 10^{-4}$) in the mean amplitude for the dominant 16 Hz frequency, but only in two accelerometers ADC2 and ADC5 (side-to-side motion). These observations are summarized in Figure 15. For ADC2, the amplitude drops from 89.22 dB to 81.69 dB, and for ADC6 it is reduced from 92.19 dB to 88.70 dB when the Mogensen unit is starting to fail. The change in other accelerometers for amplitude is marginal and not significant. These changes happen at 4:00 hours already before the total failure event at 8:00 o'clock.

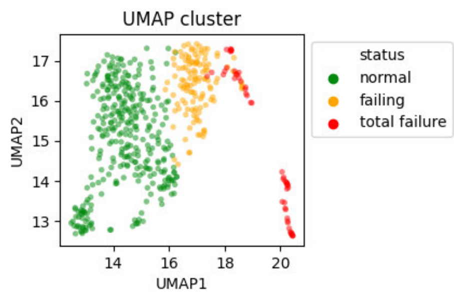

FIGURE 14. The first two dimensions of the UMAP showing different patterns for the failing sieve taking the data from May 2–4 when the machine was operational.

5) REPORTED EVENT OF CONVEYOR BELT FAILURE

The second event occurred on August 4^{th} that led to a complete production stop. The reason was a failure of the conveyor belt that is transporting the sieved material to the fine crusher. Here, we anticipate also seeing changes in the vibrational patterns to detect the inconsistency as early as possible. We can confirm our assumption when applying UMAP dimensionality reduction to the frequency spectra we see different clusters when the conveyor belt is failing as shown in Figure 16. Here, we also analyzed the dominant 16 Hz frequency peak for potential changes when the Mogensen separator was operational and did not

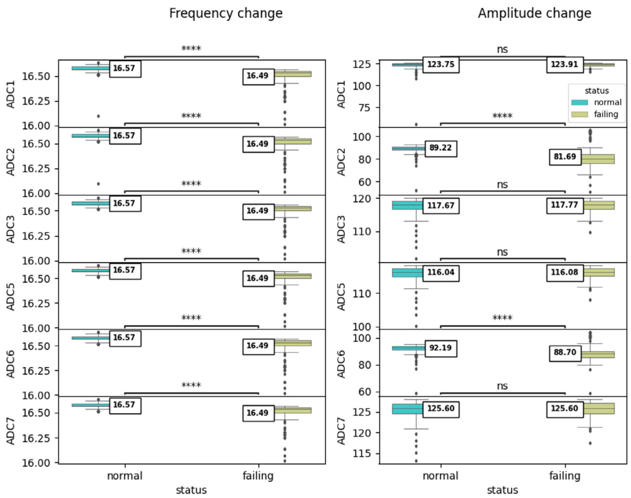

FIGURE 15. Changes in the dominant frequency and amplitude for the event of motor failure on May 3rd.

see any significant differences neither in the frequency nor in the amplitude. We also could not see any notable differences in the high frequencies of the vibration signal making it difficult to explain the cause of clustering after dimensionality reduction with UMAP.

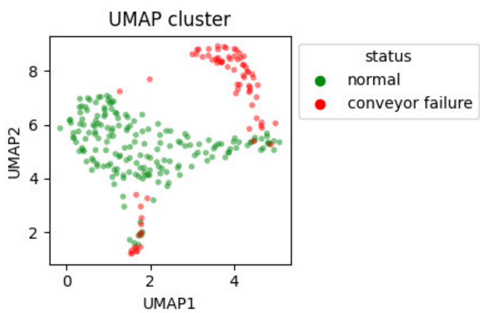

FIGURE 16. The first two dimensions of the UMAP showing different patterns for the failing conveyor belt taking the data from August 3–4 when the machine was operational.

IV. DISCUSSION

In this section, we discuss the results and the limitations of the study. In Section IV-A, we justify our choices for hardware used in the sensor installation. In Section IV-B, we present the limitations that were identified during data collection. Section IV-C discusses the issues that were identified with the chosen technology stack for data management. In Section IV-D, we discuss the chosen sampling rate as well as the findings from our statistical evaluation of the vibration data and its limitations.

A. SENSOR INSTALLATION

Much effort was undertaken to make the sensor encasing water and dust resistant. However, the mechanical durability of the cables was underestimated, causing multiple failures from abrasion and fatigue during the experiment, with subsequent data loss. Plant personnel were successfully dispatched to re-solder broken wires; however, this situation was not ideal. Besides these events, the sensor system performed as expected, withstanding other aspects of the industrial environment to deliver continuous, high-quality data throughout the test period. One point of interest was the use of double-sided tape to fasten sensors. Concerns about the longevity of this solution under constant mechanical stress and fluctuating ambient temperatures proved unfounded.

Although the motion of the Mogensen sieve is linear or a narrow ellipse, we chose to use 3-axis accelerometers, carefully aligned so that at least one channel should nominally measure zero acceleration. This proved valuable when a motor fault induced unexpected side-to-side vibrations.

The overall success of the sensor solution demonstrates that vibration sensors may be retrofitted to legacy machines with relative ease, even in a demanding environment. However, a wireless sensor solution is preferable in this setting to avoid cable failure and subsequent data loss.

B. DATA COLLECTION PIPELINE

The data collection had by design a non-continuous sampling. Data were stored as files on the SD-card and uploaded to the FTP-server if the Wi-Fi was operating normally. Data logging was paused while the FTP upload was active. This had to do with the load of the SPI-bus on the microcontroller as the SD-card and the Wi-Fi shared the same SPI bus. To maintain a very stable sample rate, this was the best solution. Sometimes several files had to be uploaded due to previous Wi-Fi problems. This was caused by the 4G router having communication problems with the 4G network. This made data analysis unnecessarily complicated and error-prone. Nevertheless, we could show that the proposed approach is sufficient to collect vibration data at a relatively high sampling rate of 1 kHz and simultaneously store the data in the cloud. Further, the gaps in the data acquisition can be avoided by either making use of the multi-threading capabilities of the micro-controller or reducing the sampling rate such that the acquired data can be sent in very small chunks to minimize the communication overhead.

C. DATA MANAGEMENT AND DATA PREPROCESSING

We noticed that the architecture of the time-series database InfluxDB significantly slows down data retrieval when querying extensive time series datasets over long periods. Hence, alternative databases designed for large-scale numerical data, such as Clickhouse, should be considered in this context [25].

The preprocessing of data poses high memory requirements when working with fully sampled resolution of the frequency spectra. Hence, we suggested sub-sampling of the spectrogram down to 1000 samples per minute per accelerometer. This leads to information loss when trying to detect subtle frequency changes in the range of 0.1 Hz but still allows detecting clusters after dimensionality reduction with UMAP.

D. PREDICTION CAPABILITIES FROM VIBRATION PATTERNS

Statistical data analysis after dimensionality reduction with UMAP showed clustering for different particle sizes. The amplitude and the frequency of the dominant vibration spectra at 16 Hz were not affected. This can be explained by rather powerful driving motors that are not easily affected or disturbed by external factors. The clustering after dimensionality reduction indicates that there is information in higher frequency spectra, which was also confirmed by a multinomial logistic regression model that was able to predict the particle size. Nevertheless, further analysis is needed to investigate which spectra are contributing to the prediction of the currently separated material. On the other hand, we could show that when using the sieving speed as an indicator of whether the separator has any material inside, it correlates with clusters of the frequency-based features after dimensionality reduction with UMAP.

When investigating the influence of the events on the vibration patterns, it was possible to see changes in the dominant frequency, as well as in its amplitude, already four hours before the catastrophic motor failure. This shows that observing the vibration of the separator is a valuable indicator for fault prediction. Also, the changes in the dominant frequency are on the order of 0.1 Hz, which justifies the need for the high-frequency sampling rate of 1 kHz. This could be compensated for by the changes in amplitude that are already noticeable at lower sampling rates.

However, it was not possible to predict another unwanted event of conveyor belt failure. It was not possible to see any changes in the vibration patterns, as the conveyor belt is not directly connected to the separator, and the accumulating material did not have any effect on the vibration pattern of the separator. The sieving unit vibrates at a frequency of 16.5 Hz. Given our evaluation, it is beneficial to sample at frequencies roughly two decades above the fundamental to pick up subtle changes in the higher frequencies and to resolve frequency shifts on the order of 1%. Further experimental investigation is needed to determine the frequency spectrum of relevant features, and from this, to determine the best trade-off between sampling rate and condition uncertainty.

In summary, we demonstrated the capability to detect significant failures, such as motor malfunctions, by monitoring alterations in the dominant 16 Hz frequency component. Furthermore, our findings support the feasibility of constructing a statistical model for assessing the operational status of the Mogensen material separator by leveraging spectral vibration characteristics.

V. SUMMARY AND FUTURE WORK

The work presented in this paper highlights the importance of digitization and data analysis in the mining and metal processing industries, particularly through the use of sensor vibration data to predict critical events before they impact production throughput and to identify machine states for legacy equipment. Specifically, this paper reports:

1) Development of a low-cost, high-performance vibration sensing solution: We designed and developed a low-cost, high-performance vibration sensing solution that can be deployed in real industrial settings. This solution is cost-effective and reliable, making it accessible to small and medium-sized enterprises that cannot afford expensive vibration sensing systems.
2) Installation of the sensing framework in a real industrial setting in a harsh environment: The sensing framework was installed in a real industrial setting under harsh conditions. This provided an opportunity to test the performance of the vibration sensing solution in a realistic and challenging environment.
3) Collection and management of high-density vibration data: The collected data was of high density, and we successfully persisted it in the cloud. The collected data served as the basis for further analysis where we could show that it is possible to predict failures before they cause more catastrophic damage and lead to unwanted downtime of the facility.
4) Statistical analysis of collected data which showed its potential to detect critical events and identify patterns related to machine states: The collected data was analyzed statistically to identify patterns related to machine states. This analysis has shown that the vibration sensing solution has the potential to detect critical events and identify machine states.
5) A subset of collected data is made publicly available for non-commercial use. The data covers a full 18 days, including two critical events. We hope that the researchers' community will benefit from this dataset and be able to use it in their own work.

The continuous observation of the vibration patterns could potentially help the site process engineer react to such events earlier.

Future work includes a deployment strategy of the analytics pipeline that consists of a simple dashboard for the process engineer to monitor the current vibration patterns and compare it live with vibration signals previously labeled as corresponding to normal operation. Our preliminary analysis showed that training a statistical model could provide additional information to the operators and possibly predict unwanted behavior. The Mogensen separator where the data was collected from has recently been removed from the factory, and the production process has changed thereafter, making it unfeasible to deploy such a dashboard in the Bjølvefossen plant at this stage. Hence, a prospective validation study with the presented data is currently unfeasible.

In addition to dust-, water-, and EMI-proofing, attention to mechanical durability must be paid when designing sensors for moving machines such as a shaking separator. Elastic cable insulation and flexible shielding (braided shields are better than foil) will reduce fatigue. Well-designed cable installation will reduce or avoid mechanical abrasion.

Additionally, it is crucial to collect background vibration data to effectively distinguish the signal originating from the machine, where the sensor is installed, from the vibrations introduced by surrounding machinery. This practice would ensure accurate interpretation of detected vibration patterns.

Furthermore, we emphasize that domain knowledge and understanding of the production process are crucial to be able to analyze the collected data. Therefore, very good collaboration with factory personnel (e.g., site engineers) is absolutely essential for a successful experimental set-up and data evaluation.

With the above experience, a follow-up experiment has been initiated at a similar machine at the Elkem Salten plant. Here, the whole pipeline from data collection to analytics on premise and prediction of events through a previously trained statistical model will be demonstrated. Multi-threaded functionality has been implemented to allow gap-free data. The cable solution has been re-designed, with more flexible materials and greater attention to fastening.

Benchmarking our results against an existing fault detection system would be another important direction; however, Elkem's separators currently lack such a system. Some manufacturers are starting to offer vibration-based condition monitoring, and our communication with one of them, Mogensen, revealed that they also offer rudimentary statistical data analysis. These separators have long lifespans, making retrofitting commercially and scientifically interesting. Exploring benchmarking with existing systems could be a future research direction as these systems become more common at Elkem plants.

Overall, this work has contributed to the development of low-cost, high-performance vibration sensing solutions for industrial settings. The results of this study can be used to improve machine maintenance and prevent downtime, which can have significant economic benefits for businesses.

VI. DATA AVAILABILITY

A data sample consisting of 18 full days, including the two events reported by the process engineers, is publicly available for noncommercial use on Zenodo.[7] More data may be shared upon request.

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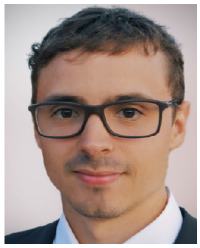

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