Tampere University

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# PROCESS MONITORING OF DEMOLITION WASTE RECYCLING CRUSHING

## Feasibility study

Master's Thesis
Faculty of Engineering and Natural Sciences
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# ABSTRACT

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Process monitoring of demolition waste recycling crushing: Feasibility study
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Demolition waste is produced when buildings or other infrastructure approach the end of their life and are demolished. To support the objectives of circular economy and financial interests, demolition waste can be processed to produce recycled aggregates and by-products using crushing and screening equipment. Due to the nature and components of the demolition waste, the crushing and screening process is subject to different disturbances, which can compromise the efficiency of operation along with other negative effects.

Directions for future development of the machinery for processing demolition waste have sparked the need to research the possibility of the equipment achieving a level of awareness on the state of the process. Ultimately, the crushing and screening plant could detect the problematic process state in an early phase and avoid serious consequences that might result from for example a total blockage of the machine.

This thesis researches the subject with several methods. A literature review was done to collect information on the subject and to get familiar with different approaches used elsewhere in the industry. An interview study was conducted to gather existing knowledge about the demolition waste crushing process and different failure types that may occur during the process. Information from these two phases were used to build understanding on monitoring the crushing and screening process. Finally, an empirical part of the study was carried out, consisting of a measurement campaign on a real-world process, and a failure case -based analysis for the measurement data.

As a result from the interview study and follow-up analysis, an overview of the demolition waste crushing process and its possible failure modes was formed. The scope of the thesis was limited to track-driven impactor crushing plants, and the results and analysis maintained this focus as well. A total of 11 failure modes were identified, along with their possible causes, root causes and effects on the process.

The measurement campaign was planned with objectives derived from the scope of this thesis as well as interests within a wider scope. Three working days of plant operation were captured using data acquisition equipment and microphones, accelerometers, existing signals on the control system of the plant, as well as additional mechanical sensors. The data was analysed on a failure case -based approach, utilizing all information gathered in the previous phases.

Results of the analysis indicate that detecting anomalies from the crushing process can be done using data from audio-, vibration-, and other domains, but performance greatly depends on the type of process failure and the nature of associated phenomena, also being dependent on correct sensor selection and placement. Different data types were demonstrated to be useful in the analysis, but the overall picture is governed by variability in the process and possible ways it can fail. In the literature, modern deep learning -based methods were suggested as a solution to combat the complexity, but they could not be included in the scope of this work.

Keywords: Demolition waste, aggregates, process monitoring, anomaly detection, fault detection and diagnosis, horizontal shaft impactor

# TIIVISTELMÄ

Atte Juvonen
Rakennusjätteen kierrätysmurskausprosessin valvonta: Toteutettavuustutkimus
Diplomityö
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Purkujätettä syntyy, kun rakennuksia tai muuta infrastruktuuria puretaan niiden tultua käyttöikänsä päähän. Purkujätettä voidaan kiertotalouden tavoitteisiin vastaamiseksi ja taloudellisista syistä hyödyntää tuottamalla siitä kierrätettyä kiviainesta murskaus- ja seulontalaitteilla. Purkujätteen luonnostaan sisältämien ainesosien vuoksi sen murskaus- ja seulontaprosessi on häiriöherkkä, aiheuttaen mahdollisia negatiivisia vaikutuksia, kuten ongelmia tuotannon tehokkuudelle.

Purkujätteen murskauslaitteiden tulevaisuutta pohdittaessa esille tulee tarve tutkia mahdollisuutta, että koneet kykenisivät valvomaan oman prosessinsa tilaa. Tämän kaltainen ominaisuus mahdollistaisi toiminnan, jossa murskaus- ja seulontalaitteet tunnistaisivat prosessissa kehittyvän ongelmatilanteen aikaisessa vaiheessa ja kykenisivät toimenpiteillään välttämään ongelmatilanteesta mahdollisesti aiheutuvat vakavat seuraukset, kuten koko laitoksen tukkeutumisen.

Tässä diplomityössä aihetta tutkitaan usealla tutkimusmenetelmällä. Kirjallisuuskatsauksessa kerätään tietoa aiheesta, sekä tutustutaan teollisuudessa käytössä oleviin menettelytapoihin. Työn osana järjestetyssä haastattelututkimuksessa kootaan purkujätteen murskausprosessista ja sen aikana esiintyvistä ongelmatilanteista olemassa olevaa tietoa. Näiden vaiheiden aikana kerätyn tiedon perusteella pyritään rakentamaan ymmärrystä purkujätteen murskausprosessin valvonnasta. Lopuksi tutkimuksessa toteutetaan käytännön osuus, joka koostuu todellisen murskausprosessin toimintaa tarkastelevasta mittausjaksosta, sekä ongelmatilannetapausten pohjalta tehdystä mittausdatan analyysistä.

Haastattelututkimuksen ja siitä kerätyn aineiston analyysin perusteella työssä muodostettiin kokonaiskuva purkujätteen murskausprosessista ja sen mahdollisista vikatilanteista. Työssä aiheen käsittely rajattiin koskemaan tela-alustaisia impaktorilaitoksia, ja myös tulokset keskittyvät tähän konetyyppiin. Kaikkiaan 11 prosessin vikatilannetta syineen, juurisyineen ja vaikutuksineen tunnistettiin haastatteluaineiston perusteella.

Mittausjakso suunniteltiin tämän työn vaatimusten, sekä muiden tavoitteiden pohjalta. Mittausjaksossa kerättiin ääni-, värähtely- ohjausjärjestelmä-, sekä muuta anturidataa kolmen työpäivän ajalta koneen aidosta käyttötilanteesta. Dataa käsiteltiin yksittäisiin vikatilannetapauksiin perustuvalla lähestymistavalla kaikkea aiemmissa vaiheissa kerättyä tietoa hyödyntäen.

Analyysin tulokset viittaavat siihen, että erilaisia murskausprosessin häiriötilanteita voidaan tunnistaa sekä ääni-, värähtely-, sekä muuntyyppiseen dataan perustuen, mutta tehtävästä suoriutuminen riippuu vahvasti ongelmatilanteen tyypistä ja siihen liittyvistä ilmiöistä, ollen myös riippuvainen sopivasta anturityypistä ja anturin oikeasta paikasta. Ongelmatapauksia analysoimalla voidaan todeta käytettyjen erilaisten datatyyppien olevan hyödyllisiä, mutta kokonaiskuvaa hallitsee sekä prosessin, että ongelmatilanteiden vaihtelevuus. Kirjallisuudessa monimutkaisuuden ratkaisuksi esitetään moderneja syväoppimiseen perustuvia menetelmiä, mutta niiden tutkimista ei voitu sisällyttää tämän työn rajaukseen.

Avainsanat: Purkujäte, kiviainekset, prosessin valvonta, poikkeamien tunnistus, vikatilanteen tunnistus ja diagnosointi, vaaka-akselinen impaktorimurskain

# PREFACE

Writing a master’s thesis feels something like climbing on top of a huge hill on a mountain bike: planning ahead, going around sections that are too steep or rocky, going slow enough and keeping a steady pace are all of great help. With the cringe-worthy allegories out of the way, this project has definitely taught me to be a better mountain biker.

The research shown in this thesis was carried out at the Metso Corporation Tampere office and factory in Finland. Nothing like this would have been possible without the contribution of the company and many people, and I would like to thank everyone involved in the process. Special thanks go to M.Sc. Juhamatti Heikkilä for the interesting topic and guidance along the work. Also, thank you to M.Sc. Henri Siiskonen for the help in planning and implementing the measurements, as well as in chasing down the corrupted USB-drives and the sneaky data logger buffer settings. I would also like to thank the examiners of this thesis, Prof. Kari Koskinen, and M.Sc. Jouko Laitinen.

Many people have also been important for me in the life outside of work during the process of writing this thesis, and the years before that. On the day I started my mechanical engineering studies, I met a group of people who have stayed in my life throughout the years, ensured that Mondays have been something to wait for, and always been there for support. Thank you to the members of the honourable Maanantaisauna, our legacy will never be gone. Also, special thanks to my family for always supporting, loving, and encouraging me, regardless of the situation.

Tampere, 9th June 2023

Atte Juvonen

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# LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| BNC | Bayonet Neill-Concelman (Connector type for coaxial high-frequency signal cable) |
| CAN | Controller Area Network |
| CDW | Construction and Demolition Waste |
| CSV | Comma Separated Values (File type for plain text data storage) |
| DAQ | Data Acquisition |
| DC | Direct Current |
| DFT | Discrete Fourier Transform |
| FDD | Fault Detection and Diagnosis |
| FFT | Fast Fourier Transform |
| FMEA | Failure Mode and Effects Analysis |
| HSI | Horizontal Shaft Impactor (Crusher type) |
| IEPE | Integrated Electronics Piezo-Electric (Technical standard for piezoelectric sensors) |
| JSON | JavaScript Object Notation (File type) |
| PCA | Principal Component Analysis |
| PLS | Partial Least Squares |
| RMS | Root Mean Square |
| STFT | Short Time Fourier Transform |
| t-SNE | t-distributed Stochastic Neighbour Embedding (Nonlinear dimensionality reduction algorithm) |
| USB | Universal Serial Bus |
| ZCR | Zero Crossing Rate |

| | |
|---|---|
| $C_f$ | Spectral centroid |
| $k$ | Frequency index |
| $N$ | Length of signal in samples |
| ${S_f}^2$ | Spectral spread / spectral bandwidth |
| $\sigma$ | Standard deviation |
| $\sigma^2$ | Variance |
| $t$ | Time index |
| $x(t)$ | Signal, function of time |
| $\bar{x}$ | Mean of the signal |
| $X(k)$ | Discrete Fourier transform of the signal |
| $\tilde{X}(k)$ | Normalized magnitude spectrum |

# 1. INTRODUCTION

The Finnish Innovation Fund Sitra (2023) describes the megatrends of 2023 with five themes: nature, people, power, technology and economy. The global ecological sustainability crisis is one of the factors connecting these themes together, and the role of technology, digital world and data is also expanding to strike more and more people, fields and subjects. European Commission (2022a) also connects the two in their 2022 strategic foresight report, for example by mentioning the role of digital technologies in achieving climate neutrality and reducing pollution. Smarter systems come with the cost of increased complexity, but meeting the growing demands is often only possible by harnessing the power of digital solutions. This leads to improving the current systems in terms of energy efficiency, reliability and level of automation.

The modern world relies heavily on human-built infrastructure. Roads, railways, bridges and other structures enable transportation of people and goods. Buildings and other facilities are built to provide space for life, work and free time. The structural backbone for these are in many cases stone-based aggregates, whether it is the primary material for concrete or asphalt, railway ballast or material for building foundation for structures. Aggregates are produced from different raw materials using heavy equipment such as different crushers and screens.

While more and more infrastructure is built, nothing lasts forever and some of the old buildings and other structures must be demolished for various purposes. While building new infrastructure requires aggregate production, demolishing the old structures is connected to everything mentioned before with recycling crushing. By processing the demolition waste using crushing and screening equipment, the need for locating the demolition waste on a landfill disappears, while recycled aggregate is produced along with secondary process output streams such as ferromagnetic materials used for reinforcing the demolished structures. Recycled aggregate can replace the one manufactured from virgin raw material in some applications, depending on the regulations and test results of the product.

The demolition waste crushing process can be carried out with few types of different equipment, including different crushers, screens and other bulk material handling equipment. The focus of this thesis is put on a mobile impactor crushing plant. The plant consists of several process components, and can produce recycled aggregate independently. An example of a such crushing plant is shown in Figure 1.

***Figure 1.*** *A mobile horizontal impactor crushing plant with a screen (Metso Outotec, 2022c)*

Characteristics of the mobile demolition waste crushing process are discussed later, but the process is known to be vulnerable and one of the most difficult of all aggregate production processes. Processing the heterogenic demolition waste is not straight-forward and comes with several possible ways of things going wrong. As the process is naturally subject to disturbances, or *anomalies*, efficient operation of the plant is threatened, resulting in various higher-level problems. First, unreliability of the process might act as a deterrent, slowing down the wider adoption of the recycling crushing process. This causes a negative impact for sustainability development and harms the manufacturer of the plant. If the process is operated despite the risk, every interruption in the operation harms the company operating the machine with lost profit, increases unnecessary manual work, might pose safety threats to the personnel, and decreases the energy efficiency of operation.

Along with the trends in circular economy and digitalization, key drivers for increasing the amount of recycling are regulations. In the area of European Union, 70 percent of non-hazardous construction and demolition waste by weight should be recycled and used in a suitable application (European Commission, 2022b).

## 1.1 Research problem, objectives, and methods

With the presented background, a need arises to research the possibility of harnessing digital technology to monitor the recycling crushing process. In the current state, the plant operation must be very carefully monitored by the operators, often requiring ground personnel that are ready to act and alert others upon an anomalous event. Some of the anomaly events are very serious. For example, an event blocking the material flow inside the plant might take less than a minute to develop, and result in up to 8 hours of manual work to resolve. With possible future development direction of even more enclosed machines with weakened possibility for visual monitoring of the process state, digital process monitoring solutions could act as an assist for the operators to convey information about the state of the machine and process. These solutions could possibly also simultaneously monitor the machine condition and predict possible component failures before their escalation.

As the development for such system is in an early phase, this thesis conducts a feasibility study on the subject with a broad problem-setting. The research questions for the work are formed as follows:

1. What are the typical process anomalies in the demolition waste recycling crushing process?
2. How can data analysis of the plant control system data be utilized in detecting these anomalies?
3. How can audio signal analysis be utilized in detecting these anomalies?
4. How can vibration signal analysis be utilized in detecting these anomalies?

As the research questions show, the work revolves around the knowledge of the possible anomalies in the demolition waste recycling crushing process. This information is considered to exist in the company, at least to a certain extent, but is scattered around in the organization. To build a foundation to the research, interviews are conducted to investigate the demolition waste crushing process and its anomalies in a more systematic way.

The three remaining research questions include a massive selection of scientific fields and methods from signal processing and machine learning to a dedicated field studying fault detection and diagnosis. Literature review is done to gather information about the subject, provide theoretical answers to the research questions, and to prepare for the empirical part of the work. A big part of the thesis is a practical study in demolition waste crushing field conditions. A measurement campaign is conducted to collect data that is later processed and analysed to get a practical view on the problem, and to answer the research questions from empirical point of view. The measurement campaign is partially formed by the research questions and includes a wide range of measured quantities. The existing control system of the plant provides some data and information about the state of the process, but this data is augmented with additional mechanical measurements, as well as vibration- and audio measurements. One of the research interests is to investigate the possibilities of audio measurement in terms of monitoring the process. Other interests for utilizing the data from the measurement campaign exist as well, and the needs are considered in the implementation phase of the measurements.

## 1.2 Thesis structure

The structure of the thesis is divided into four parts. The first part consists of chapters 2 and 3. Chapter 2 builds the background by reviewing existing research and key concepts in the area of fault detection and diagnosis and monitoring of industrial processes, as well as explaining theoretical concepts found later in the work. Chapter 3 describes the demolition waste recycling crushing process, which is considered in this work, and builds understanding on the working principle of the mobile impactor crushing plant.

With the background knowledge on the subject, the second part addresses the first research question, and is presented in chapter 4. Planning, execution, and results of the interview study are shown, and based on the interview results, the process anomalies are analysed in terms of their causes, actual root causes and effects on the machine operation.

Chapter 5 presents the third part of the thesis, the measurement campaign. Measurements were done on an actual operational machine in real conditions, which provides both advantages and disadvantages. In this chapter, the planning of the measurements is described, followed by description of the application, measurement hardware and actual measurement implementation.

Finally, chapter 6 presents the analysis of the data collected in previous part of the work. Knowledge gathered during the work is harnessed, and three anomaly cases are selected to be analysed. The results are presented in a way to build a general picture on what can be done in terms of possible anomaly detection system, and on the other hand what are the challenges for developing such a system.

After the main parts of the work, conclusion wraps up the findings and combines the observations made throughout the process.

## 1.3 Target company

The target company of the thesis is Metso Corporation, previously known as Metso Outotec and Metso Minerals. Metso is a global company in aggregate- and mining business, and a major manufacturer of aggregate production equipment. The company is headquartered in Finland, present in over 45 countries and employs over 16 000 people. Metso states sustainability as their strategic priority and promises to support the transition towards a world with less carbon dioxide emissions and more safety. Later in this work the company is referenced to as *target company.*

# 2. INDUSTRIAL PROCESS MONITORING

Industrial processes include an extensive collection of different operations, utilizing one or more steps to modify bulk material or individual items, refining them, and adding value. A process might encompass multiple steps, which can sometimes be defined as their own sub-processes, depending on the scope of examination. In the aggregate production industry, a process might include several steps, such as extracting raw material from the bedrock with explosives, primary crushing, secondary crushing, tertiary crushing, and screening. Depending on the application, each of the steps could be defined as an individual process, as for example the chain may be built up of several individual and independent machines, which are working together to produce the final product. Another example of an aggregate production process includes one crushing stage and one screening stage and is contained in a single mobile unit. The machine in the scope of this work belongs in the latter category.

It is somewhat self-evident that such processes benefit from problem-free operation. Disturbances might cause a degradation in the quality of the product, loss of precious production capacity, or require additional work from the operators. More severe problems could damage the equipment used, or in the worst case, harm the people. If anomalous behaviour can be detected, many of these situations can be avoided.

The scientific field studying industrial process monitoring is often referenced to as Fault Detection and Diagnosis (FDD). As Abid et al. (2021) state, FDD has traditionally only been applied in safety-critical processes, but the growing demands for productivity and operational reliability are acting as driving forces to extend the monitoring to a broader range of equipment or systems.

In this chapter, process monitoring is researched through a literature review. The subject is very broad, and thus it is not reasonable to address it comprehensively in the scope of this thesis. The focus is limited to overview of the subject and concepts relevant in this work.

## 2.1 Importance of system knowledge

When developing fault detection and diagnosis for any given process, the first step is to obtain so-called *a priori* knowledge about the system (Abid et al., 2021). This knowledge includes information about system representation and redundancy as well as types of faults and malfunctions and can be described to contain detailed knowledge about the nature and dynamics of the system or process.

System representation describes a way in which the system or process is modelled or somehow shown in an abstract form to help in understanding the behaviour of the system. System knowledge can be presented in explicit or implicit form. For example, if a system can be easily described in a form of a mathematical or empirical model, the system representation can be stated to be explicit. Implicit forms of system representation include graphical approaches, artificial neural networks or expert systems consisting of different rules and heuristics. The representation of the system also is a big part in deciding the class of realizable fault detection methods for the system. (Abid et al., 2021)

Another important factor when considering FDD development is system redundancy. System redundancy is directly linked to the reliability of the operations of the system and can be created in different forms. Abid et al. divide the system redundancy into categories, which are physical redundancy, analytical redundancy and software redundancy or structural redundancy. If the system is physically redundant, it might contain additional components working in parallel and providing a backup in case of malfunction. Analytical redundancy includes relationship constraints and functional dependence among system variables, providing an inconsistency check between expected and actual behaviour of the system. Structural or software redundancy refers to having multiple strategies for the same function, working in parallel or being dynamically activatable to counteract any malfunction in the system. (Abid et al., 2021)

Finally, fault and malfunction types of the system should be considered. Types of possible malfunctions depend on the system in question, and the scope of the FDD system being developed. The faults can be classified to different classes based on the type of fault, or nature and dynamics of the faults. Different fault types can be for example software- and hardware faults. Classification based on the dynamics of the faults may include classifying the faults as transient, intermittent, incipient, and permanent faults, which describe in which way the fault emerges or is detectable. (Abid et al., 2021)

## 2.2 Process data collection

Some form of collected information is a prerequisite to process state monitoring and fault detection. Depending on the process and its level of instrumentation, a number of parameters is typically measured and used for different purposes even without any fault detection systems. Data collection for fault detection purposes is carried out in similar way to any process instrumentation, and typically, FDD setup uses a variety of different sensors such as current, voltage, temperature, pressure, position, force, vibration, et cetera (Abid et al., 2021).

In this sub-chapter, process data collection is addressed, with focus on the system and process in question.

### 2.2.1 Process data collection in general

Many of the industrial processes involve handling of individual items, bulk material, liquids, or gases. As a result, the processes naturally contain measurable physical quantities. A large variety of different sensors are used to convert these quantities into analogue or digital signals. Fraden (2016, p. 9) presents different stimuli that can be measured, and the main categories are:

1. Acoustic
2. Biological
3. Chemical
4. Electric
5. Magnetic
6. Optical
7. Mechanical
8. Radiation
9. Thermal and
10. Other

Each category is further divided into sub-categories, and as the variety of the categories demonstrates, almost everything can be measured.

Different categories and physical quantities have different properties. Temperature, hydraulic system pressure, rotational velocity, or similar variables are often non-periodic and biased, especially if the process has a steady or relatively steady state. Certain quantities are measured as oscillating signals with no DC-bias. For example, vibration signal is measured with accelerometers, and the output of the accelerometer oscillates around zero, while the information content of the signal is divided along a broad frequency spectrum. Both types of data can be collected with similar methods, but when any high-frequency phenomena are involved, factors like sample rate, aliasing and possible data transfer method performance must be carefully considered.

### 2.2.2 Control system data collection

Controller Area Network (CAN) bus is a widely used electronic communication bus that is defined by the ISO 11898 standards. The CAN bus network consists of different nodes, which are connected to the bus. All nodes in the CAN bus are subject to all the communication happening in the bus, making the CAN bus a broadcast type bus. (Kvaser, 2022)

The CAN protocol defines several types of physical layers for the implementation of the CAN bus hardware. The most common type of these layers is defined in the ISO 11898-2, consisting of a balanced, two-wire signalling scheme. The two-wire physical implementation allows the bus to be relatively tolerant to electromagnetic disturbances, as the signal is transmitted as a voltage differential between the two wires, and the wiring is carried out in a twisted pair configuration. CAN protocol also defines several ways of detecting errors in the communication, increasing the reliability of the transmission. (Kvaser, 2022)

All communication in the CAN bus is based on messages, which are sent to the bus by a node, and received by every node connected to the bus. The messages are short, with maximum utility load of 94 bits, and are transmitted with a priority. The priority of the messages is used to resolve possible conflicts in a situation where two nodes start the transmission to an idle bus at almost the same time. In this situation, the node sending a lower priority message will stop the transmission when it recognizes a higher-priority message being sent simultaneously. While single messages are short and contain a small amount of data, the CAN bus supports transmission speeds of up to 1 Mbit / second. (Kvaser, 2022)

Modern vehicles and mobile working machinery include an increasing number of sensors, electronically controlled actuators, human interfaces, and many other forms of automation hardware. Due to the increasing complexity, using a bus type communication has become standard practice among the manufacturers, as every different device can be connected to the bus as nodes, and individual wiring for different functions is not needed. CAN protocol has established a stable position as the go-to bus communication protocol between the automation components in mobile machinery and vehicles.

Mobile crushing and screening plants manufactured by the target company also utilize CAN bus as their communication protocol. The main CAN bus of the mineral processing plants carries the information produced and used by the automation system of the plant. As a result of the CAN bus being broadcast -type, messages transmitted through the bus can be monitored by connecting a CAN-compatible device to the bus.

Monitoring the CAN bus of the plant is an easy way of acquiring several measurement- and control signals that are directly or indirectly linked to the operation of the machine. The main principle of the CAN bus being a prioritized control system communication protocol limits and directs the types of data on the bus. The bus has a defined speed and capacity, and the number of messages must stay below the overloading limit of the bus. Signals closely connected to the automation of the core functions are typically sent to the bus with a fixed interval, but the capacity of the bus and the large number of signals limits this interval. Due to these limitations, certain types of raw data can be effectively sent through the can bus, but other data types are not applicable to be transmitted through the CAN bus.

Signals transmittable through the CAN bus include signals from relatively slowly changing phenomena. Physical quantities such as temperatures, rotational velocities or material levels do not typically include usable high-frequency content, and the capacity of the CAN bus communication allows for comprehensive monitoring of these quantities. Borderline cases include quantities such as mechanical power or hydraulic system pressure. Information about these phenomena is mostly used based on the low-frequency components of these signals. However, depending on the application, these signals could carry useful information through their higher-frequency components. These components cannot be directly transmitted through the CAN bus.

Some of phenomena, such as mechanical vibration and sound, naturally have their information content distributed over a broad range of frequencies. With the limited capacity of the CAN bus, these signals cannot be transferred using the bus, and therefore require specialized hardware for signal acquisition or processing.

### 2.2.3 Vibration data collection

Vibration is defined as “oscillation about an equilibrium point” (Kutz, 2013, p. 367), and is present in exceptionally wide range of different physical systems and applications across a myriad of domains. In general, vibration can originate from many different sources, and therefore vibration data can be used for various purposes. Kutz (2013, p.368) lists possible use cases for vibration measurements, and states that one application for vibration measurements is determining the dynamic response of a machine from forces generated during operation. Other notable applications include monitoring the condition of the machine components, such as identifying damaged or unbalanced shafts, faulty bearings or gears, and loose mechanical parts (Kutz, 2013, p.368).

Vibration of a structure is commonly measured using an accelerometer. Accelerometer is a type of sensor that utilizes some form of spring-mass system, which is attached to the housing of the sensor. The operating principle of accelerometers is based on the relative displacement between the mass of the spring-mass system and the housing of the accelerometer. When the sensor is exposed to acceleration resulting from the sensor being fixed to the vibrating surface, a dynamic force is applied on the mass, resulting in displacement of the mass from its equilibrium point. Different accelerometer types utilize different methods for measuring the relative displacement of the mass, and the types have differences in frequency range, sensitivity, and measurement resolution. Three basic types of accelerometers are piezoelectric, piezoresistive and capacitive accelerometers. Different ways of mounting the accelerometer to the vibrating surface may be utilized, including threaded mounting, different adhesives, or magnetic mounting. The measurement performance may be limited by the mounting method, as for example weaker magnetic mounting can limit the available frequency range. In very light structures, the mass of the accelerometer might also disturb the results and should be taken into account. (Kutz, 2013, p. 398 - 400)

Vibration measurements are used widely for different diagnostics and monitoring purposes. For example, Mohd Ghazali and Rahiman (2021) review several different approaches in the literature, where vibration measurements and different techniques for data analysis have been used for condition monitoring of different machinery. As a different example, Klaick et al. (2018) have carried out a study on using vibration measurements and feature extraction[1] along with a classification method to monitor the process of rock drilling. The results indicated substantial potential in using vibration and extracted features in tool wear monitoring in the mentioned study.

### 2.2.4 Audio data collection

Sound pressure is defined as “small deviations of pressure from the ambient generated by sound waves” (Kutz, 2013, p. 436). The pressure deviations are often generated by a vibrating object or other sound source. When the sound-producing surface is vibrating, the surface produces condensations and rarefactions in the density of the air or other medium, and the local lower- and higher-density areas form the sound waves in the air or any other medium that is surrounding the sound source. An illustration of the sound pressure and corresponding density fluctuations is shown in Figure 2.

[1] Discussed in chapter 2.3.2

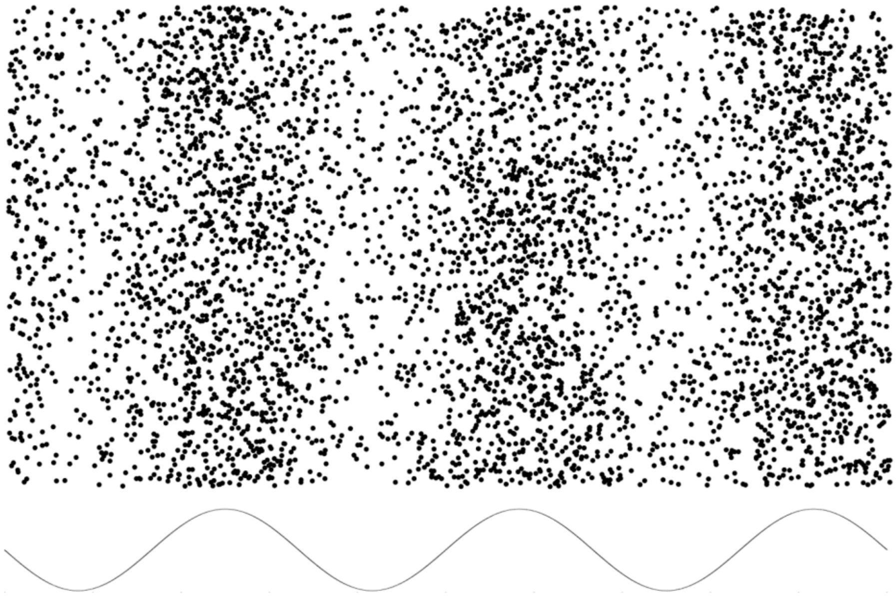

***Figure 2.*** *Principle of sound pressure. Sound wave is shown as the sinusoidal wave and corresponding particle density is illustrated above.*

Sound pressure is measured with a sensor called a microphone. Microphones exist in many different forms and are commonly found for example in consumer electronics. For scientific sound pressure measurement applications, special measurement microphones are used. Measurement microphones can be divided into free-field- , pressure- and random-incidence microphones, depending on the application they are designed for (GRAS, 2023a). The purpose of measurement microphones is to provide accurate sound pressure data, which can be collected and used for research purposes. The measured pressure data is a representation of the sound wave propagation across the point of measurement. Different measurement microphone types are available, and the selection criteria depends on the application and other measurement hardware.

In addition to vibration measurements, acoustic data collection and analysis can also be utilized in different monitoring purposes. Ubhayaratne et al. (2017) conducted a study on sheet metal stamping process monitoring in terms of tool wear using audio measurements and signal processing, and the results indicate that audio signals were significantly useful in the application. Another study was conducted, where audio measurements with accompanying signal processing and machine learning were used for metal additive manufacturing process monitoring with promising results (Hossain and Taheri, 2021).

## 2.3 Data analysis methods

Detecting abnormal states of a certain process has been widely studied. In the recent years, several reviews have been published, presenting the development in the area of fault detection in different systems. (Park et al., 2020; Abid et al., 2021; Calabrese et al., 2022; Divya et al., 2022). In addition to fault detection, the term “anomaly detection” appears in the literature (Erhan et al., 2021; Schmidl et al., 2022). With anomaly detection, Erhan et al. (2021) references to “identifying data patterns that deviate remarkably from the expected behaviour”, which indicates that the term anomaly detection refers to a more wide range of different systems and anomalies. Similar methods are discussed in both contexts, and there is no clear boundary between the two.

Another term related to the subject is *novelty detection*, which is defined by Pimentel et al. (2014) as “the task of recognizing that test data differ in some respect from the data that are available during training”. Faults and failure detection in complex industrial systems is one application domain linked to novelty detection. Pimentel et al. (2014) also states that the complexity of modern high-integrity systems leads to a situation where all abnormalities of a certain system cannot be determined before they appear, and that novelty detection offers a possible solution to this problem.

### 2.3.1 Overview of fault detection methods

Fault detection can be carried out with a large variety of techniques. Schmidl et al. (2022) express the general variety of approaches in time series anomaly detection as being remarkably high, and states that all of the approaches display individual strengths and weaknesses, making the selection of algorithm extremely difficult for a given anomaly detection task. Abid et al (2021) describe the variety of FDD techniques as wide, and state that a lot of work has been done recently for fault detection development.

The division of different approaches in fault detection and anomaly detection does not appear perfectly unanimous in the literature. In their review Erhan et al. (2021) address anomaly detection in sensor systems and divide anomaly detection techniques into conventional and data-driven techniques. The conventional techniques consist of sub-categories, which are statistical, spectral, time series analysis, signal processing and information theory. Data-driven techniques include supervised, semi-supervised and unsupervised methods, as well as deep- and reinforcement learning. Wang et al. (2022) classify fault diagnosis methods into three main categories, which are analytical methods, data-driven methods and knowledge-based methods. A major difference is that Wang et al. (2022) define statistical analysis to belong under the data-driven category.

Schmidl et al. (2022) divide 158 time series anomaly detection methods into seven categories, which are classic machine learning, signal analysis, stochastic learning, statistics, outlier detection, data mining and deep learning. The classification proposed by Wang et al. (2022) is shown in Figure 3. It is notable that only a small fraction of available methods can be shown like this.

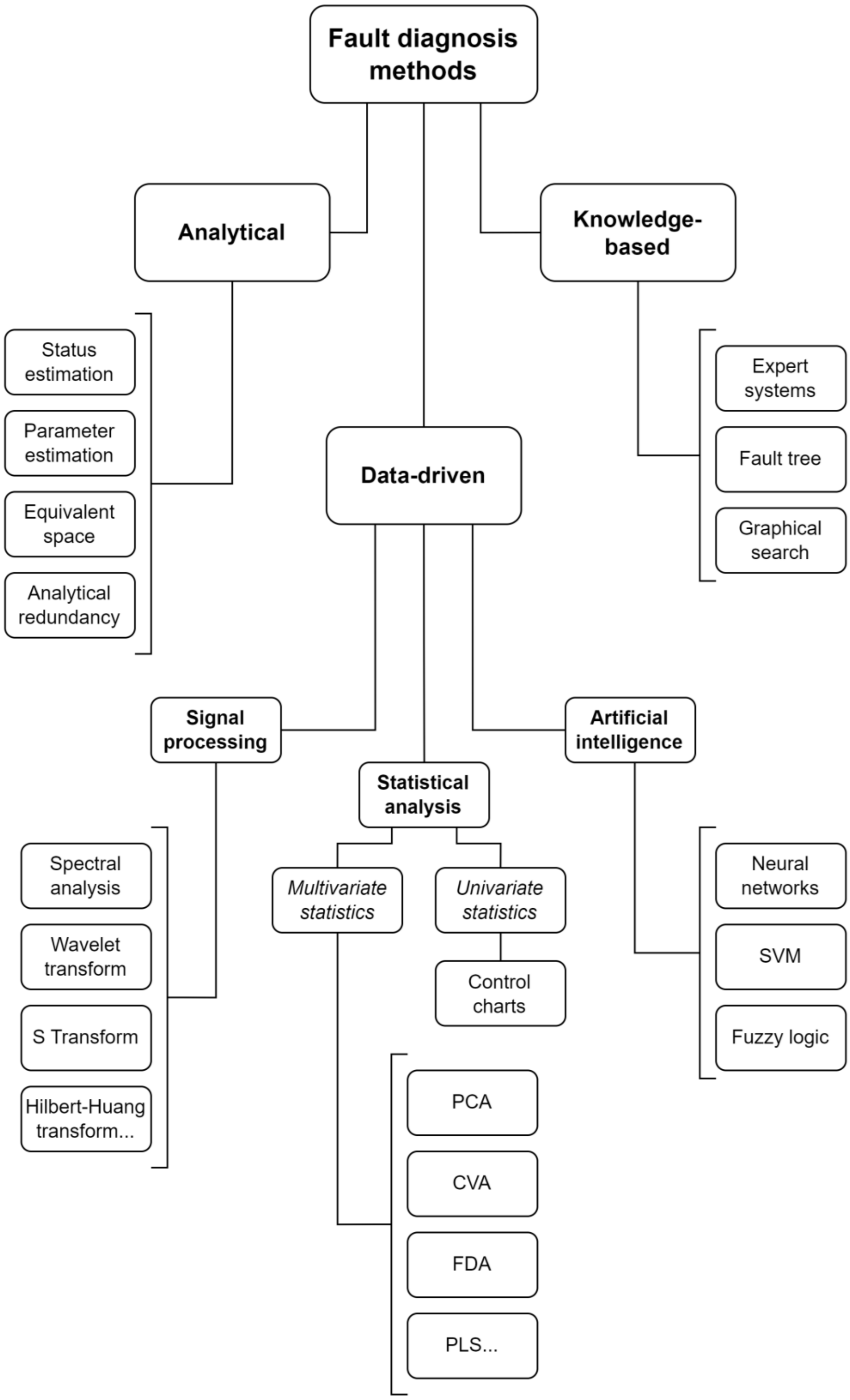


***Figure 3.*** *One classification of different fault diagnosis methods (Wang et al., 2022 p. 2)*

Analytical methods are based on an analytical model that has been constructed from the system under investigation. Physical characteristics and first principles of the system are often used in defining the analytical model. This means utilizing deep analytical knowledge about the system in question to for example estimate the system state. Analytical fault detection methods are stated as being relatively simple, and their use cases often are related to less complex systems. (Wang et al., 2022 p. 2-3) The availability of a mathematical model associated with the system is very crucial when utilizing this methodology (Satyam et al., 2022), and in addition to the physical characteristics and first principles, system identification techniques can be applied in order to produce the model.

Knowledge-based methods are used without an accurate mathematical or analytical model and rely on empirical knowledge of the process. Expert experience and historical data of the system is employed to construct different rules for fault detection. However, gathering the knowledge and experience can be in some cases considered time-consuming and even difficult. (Wang et al., 2022 p. 2-3) As mentioned in the chapter 2.1, FDD development for any given system should start with collecting a priori knowledge about the system in question. Understanding the possibilities of the system representation will set the limits for using any methods that utilize an analytical or empirical model.

While the other two categories utilize data alongside a mathematical or empirical model or rule set, data-driven fault detection establishes a data model between the input and desired output and utilizes different techniques to extract the hidden information contained in the data (Wang et al., 2022 p. 2-3). Data-driven methods can also be described to compensate the absence of an underlying mathematical model by the availability of large amounts of data and using the data to learn useful information (Erhan et al., 2021). With analytical methods being best suited to systems with low complexity and knowledge-based methods often requiring extensive experience, data-driven methods are utilized with complex systems that are difficult to model analytically, and when knowledge-based methods cannot be applied.

Wang et al. (2022) divide data-driven methods into three sub-categories. The first category includes methods utilizing signal processing. Different types of signals such as sound, images, or outcomes of monitored physical processes can be handled with signal processing methods. Erhan et al. (2021) mention de-noising and different transforms being useful in detecting anomalies. Transforms include Fourier transform, which is a common method that converts the time-domain signal into frequency domain, after which the distribution of the frequency components in the signal can be reviewed. Wavelet-based approaches are another form of signal processing that have been used in anomaly detection (Erhan et al., 2021).

Another sub-category is called statistical analysis, which is split even further into multivariate and univariate statistics. Statistical methods assume that the data points follow some statistical model, and any deviation from the model is considered an anomaly (Erhan et al., 2021). The term “univariate statistics” is used, when a single variable is considered, while multivariate statistics is used for methods employing multiple variables to differentiate the normal operational state from faulty one. Several methods are based on the principal component analysis (PCA). PCA-based methods are commonly found in the FDD literature, and are sometimes classified as spectral techniques, as Erhan et al (2021) demonstrate.

The final sub-category under data-driven methods is artificial intelligence. This term references to machines being able to perform tasks, which were previously classified as human-like, such as understanding human language or producing it. Many methods can be used to build such intelligent machines, and the technology is rapidly developing and evolving. One field in artificial intelligence is machine learning, in which data is used to teach computers using different algorithms and techniques, and eventually the computer learns to behave according to the training data. Some of the major methods in artificial intelligence and machine learning are different neural networks, which are often mentioned in the context of fault detection and diagnosis.

### 2.3.2 Feature extraction and dimensionality reduction

As demonstrated in the previous chapter, data can be used in a multitude of ways for the purpose of fault detection. While some methods may utilize the data in the raw form as it is measured, several techniques utilize different ways to condense or refine the information available from the raw data and then use the condensed information in decision-making.

Zheng (2018) defines a feature as “a numeric representation of an aspect of raw data”, found in the context of machine learning between data and models. Feature engineering on the other hand is “the process of transforming data into features that better represent the underlying problem” (Ozdemir, 2018), while feature extraction is used as a somewhat interchangeable term to feature engineering. Features can be extracted from the raw data either manually or automatically, and doing so has the ultimate goal of identifying the most discriminating characteristics in signals, which can later be used for training machine learning models (MathWorks, 2023).

Features can vary from very simple statistical features, such as minimum or maximum, to features calculated for example with very sophisticated signal processing techniques. Next, the mathematical representations of few selected features are shown, building the foundation for the analysis done in the scope of this thesis work.

When assumed discrete measured data $x(\boldsymbol{t})$ with a length of $N$, mean of the data can be calculated as shown in formula 2.1.

$$\bar{x} = \frac{1}{N}\sum_{t=1}^{N} x_t \tag{2.1}$$

Standard deviation of the data can be calculated using formula 2.2.

$$\sigma = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})^2} \tag{2.2}$$

Another measure of dispersion, variance, can be calculated as shown in formula 2.3.

$$\sigma^2 = \frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})^2 \tag{2.3}$$

Skewness describes the asymmetry of the probability distribution of the data and can be calculated as shown in formula 2.4.

$$\mathrm{skew}(x) = \frac{m_3}{{m_3}^{3/2}}, \qquad \text{where } m_i = \frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^n \tag{2.4}$$

Kurtosis is a measure of the so-called “tailedness” of the data probability distribution and is calculated with formula 2.5.

$$\mathrm{kurtosis}(x) = \frac{m_4}{{m_2}^2}, \qquad \text{where } m_i = \frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^n \tag{2.5}$$

Root mean square (RMS) is used to represent the average power of a signal and can be calculated from the data with formula 2.6.

$$\mathrm{RMS}(x) = \sqrt{\frac{1}{N}\sum_{t=1}^{N}{x_t}^2} \tag{2.6}$$

As mentioned in chapter 2.2.1, some of the measured quantities have their useful information spread along a broad frequency spectrum, and using the time domain features such as the ones shown previously is not sufficient for representing the information in a concise form. To extract information from the frequency distribution, the data can be transformed to frequency domain with the principle of the Fourier transform. When the measurements are done using digital equipment, the signals are in discrete form, and therefore a discrete Fourier transform (DFT) is used for the domain transformation. DFT can be obtained from the signal as shown in formula 2.7, and is commonly computed with the efficient fast Fourier transform (FFT) -algorithm. A related transform is the short time Fourier transform (STFT), in which the frequency spectrum is obtained for local, short sections of the signal. While calculating the DFT results in the frequency spectrum of the entire signal length, a discrete-time STFT results in time-frequency -domain representation of the signal, which can later be shown in the form of a spectrogram or similar plot, where time and frequency are represented on the 2-dimensional coordinate axes, and the amplitude is shown as colour intensity, or height in a waterfall-type plots.

$$X(k) = \sum_{n=0}^{N-1} x_n \mathrm{e}^{-\mathrm{i}2\pi\frac{k}{N}n} \tag{2.7}$$

From the frequency domain representation of the signal, a normalized magnitude spectrum can be calculated using formula 2.8, where $\mathcal{K}_+$ denotes the positive frequency indices.

$$\tilde{X}(k) = \frac{|X(k)|}{\sum_{k\epsilon\mathcal{K}_+}|X(k)|} \tag{2.8}$$

Using the normalized magnitude spectrum, spectral centroid can be calculated using formula 2.9. The spectral centroid describes the centroid of the frequency distribution.

$$C_f = \sum_{k\epsilon\mathcal{K}_+} k\tilde{X}(k) \tag{2.9}$$

The bandwidth of the frequency spectrum can be described with spectral spread, which can be calculated with formula 2.10. The value increases if the frequency distribution is wide around the centroid and decreases if the frequencies in the signal are located narrowly around the centroid.

$$S_f{}^2 = \sum_{k\epsilon\mathcal{K}_+} \left(k - C_f\right)^2 \tilde{X}(k) \tag{2.10}$$

Many other features can be calculated from measured signals. For example, Sharma et al. (2020) review a huge variety of different features that can be extracted from audio signals. One example is spectral flatness, which describes how even the frequency spectrum is. This feature is defined e.g. by Dubonov (2004), and the definition is omitted here. Another example is a feature called zero crossing rate, which is a measure of the signal zero-crossings during the reviewed period. For audio signals, mel frequency cepstral coefficients are often mentioned. They are also mentioned by Sharma et al. (2020). Similar features can be used for vibration signals (Mohd Ghazali and Rahiman, 2021), and the variety of different options is huge in vibration features as well.

Dimensionality reduction is a concept in machine learning, used for reducing the number of variables or features (Han et al., 2023 p. 71). In machine learning, the technique can be used as a part of the pipeline to reduce the number of features or variables while retaining most of the variance in the data, improving the performance or effectiveness of classification. Several linear and non-linear dimensionality reduction methods exist, and one of the most widely used methods is principal component analysis (PCA). With the PCA being a linear method, it cannot capture nonlinear relationships between the features or variables, and different non-linear methods have been developed, including non-linear PCA variations. One non-linear dimensionality reduction algorithm is called t-distributed stochastic neighbour embedding (t-SNE) (Maaten and Hinton, 2008), and according to Han et al. (2023, p. 76), it has been widely used for example for projecting the multi-dimensional representation produced by various deep learning models to a two- or three-dimensional space for the purpose of visualization.

The scope of this thesis does not include designing or testing classifiers or implementing any deep learning models, but rather focuses on the foundational elements of fault detection and process monitoring. The t-SNE algorithm has been stated to be one of the best tools for visualizing multi-dimensional data in two-dimensional scatter plots (Kruiger et al., 2017), and is used for the purpose in this work.

# 3. CONSTRUCTION AND DEMOLITION WASTE CRUSHING PROCESS

Ministry of the Environment in Finland (2018) defines Construction and Demolition Waste (CDW) simply as waste produced in construction or demolition operations. CDW can be produced in several different site types, such as different demolition sites, renovation sites and road building or refurbishment sites (Struková and Sičáková, 2016).

Increased landfill costs and growing amount of construction waste, along with new legislation and current trends, are encouraging the use of recycling equipment to produce recycled aggregates from the raw materials. The products of CDW recycling can be used for example for road construction, embankments, foundations and bulk fills, and they also have other uses. (Metso Outotec, 2022a)

Metso Outotec (2022a) divides aggregate recycling into four categories:

1. Concrete recycling
2. Asphalt recycling
3. Soil recycling
4. Slag recycling

In this thesis, the scope of study is concrete-based building demolition waste recycling, which can be placed into the concrete recycling -category. In addition to concrete, construction and demolition waste typically contains other materials as well, including bricks, wood, glass, metals, and plastic (European Commission, 2022b), and even though the focus is in concrete recycling, many of the other material types exist in the demolition waste as well.

In this chapter, the crushing process of demolition waste is described. Different components are discussed, and system representation for fault detection purposes is addressed.

## 3.1 Process description

The description of the demolition waste recycling crushing process is based on the working principle of a mobile impactor crushing and screening plant, manufactured by the target company. An illustration of the plant with the process material flow is shown in

Figure 4. The main components are also numbered roughly in the order the material flow interacts with them.

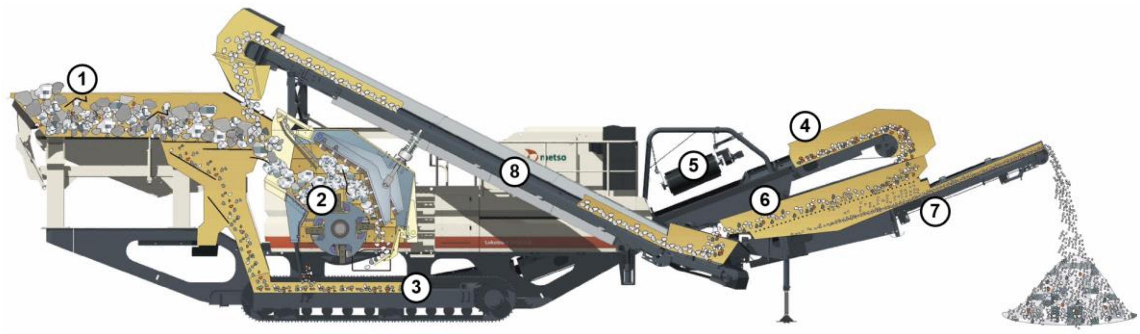


***Figure 4.*** *General illustration of a mobile impactor crushing plant operating principle (Modified from: Viilo, 2011)*

The flow of material begins from a component called vibrating feeder, which is marked in the figure with a position number 1. Commonly, an excavator supplies the feed material to the hopper of the feeder, after which it is fed into the crusher (pos. 2). The finest fraction of the feed material bypasses the crusher and is either directed to a side conveyor, exiting the process, or forwarded towards the later process stages.

Size reduction of the feed material happens in the crusher, which can be called as “the heart of the process”. The crushing plant is equipped with a Horizontal Shaft Impactor (HSI) -crusher (Metso Outotec, 2022b). After the crushing phase, material is dropped or thrown downwards onto the bottom-most component of the process (pos. 3), a vibrating conveyor, which is equipped with wear parts to withstand the abrasive effect of falling material. The conveyor is located between the mobile crushing plant’s tracks and forwards the material using vibrating motion.

From the vibrating conveyor, the material is transferred onto the main conveyor, which is marked with a position number 4. The purpose of the main conveyor is to move the material forwards in the process, and to lift the material up to enable the functionality of the next component (pos. 6), the screen. While travelling on the main conveyor, the material flows under the cross belt magnetic separator (pos. 5), which has an important role in the demolition waste crushing process. The magnetic separator removes any iron or other metals that are attracted by the magnetic field from the material flow on the belt of the main conveyor and expels them from the process using its own conveyor belt.

After the main conveyor, the material flows through the screen. The screen splits the material flow into two fractions, one of which is the final product and the other contains oversized parts of the material flow. Final product is fed through the screening media onto the product conveyor (pos. 7), and the oversized part is conveyed to the return conveyor (pos. 8), which forms a closed loop by returning the material fraction to the feed hopper.

## 3.2 Process components

Feeder is a significant component of any crushing process, as it controls the amount of feed material entering the crusher. If the feeder is not working or controlled correctly, excess material can be supplied to the crusher. Especially in the case of an impactor crushing plant, overloading the crusher can cause problems as the power available to the crusher is limited, leading to reduced capacity, or even stalling of the crusher. The operation of the feeder is based on a vibrator unit attached to the body of the feeder, which is suspended on springs. The vibration trajectory of the feeder is designed to move the feed material towards the crusher. The discharge end of the feeder includes grizzly bars, which allow the finest fraction of feed material to avoid being fed into the crusher. Feeder is equipped with hydraulically folding sides, which increase the feed hopper capacity to allow for intermittent feed material supply with an excavator.

Material size is reduced in the HSI -type crusher. An HSI crusher is based on a large high-inertia rotor with blow bars attached to it. The rotor of the crusher spins (clockwise direction in the Figure 4), which causes the feed material to hit the blow bars and be accelerated towards the breaker plates found on the inside of the crusher frame. When the material impacts with the breaker plates, it is crushed by the inertial force of the rapid deceleration. Internal structure of the crusher is further explained by Figure 5, where the material is fed from the right, and the rotor spins in an anti-clockwise direction. Metso Outotec (2022a) rates the impact crusher as ideal for soft concrete and asphalt recycling, well suited for slag recycling and usable for hard concrete recycling. Another crusher type for recycling applications is the jaw crusher, which is better for hard concrete and slag applications (Metso Outotec, 2022a). As the structure of the crusher is subject to abrasive material flow and high-energy impacts, certain parts wear down in normal operation. Blow bars, breaker plates and the inside linings of the crusher are designed as wear parts, being easily replaceable and withstanding the harsh conditions optimally. The position of the breaker plate(s) is adjustable, and the adjustment value is called the setting of the crusher. The crusher setting is one of the factors determining the particle size distribution of the crushed material.

***Figure 5.*** *Horizontal shaft impactor crusher. Model with two breaker plates shown (Metso Outotec, 2022d)*

A vibrating conveyor below the crusher is the first component that is in contact with the freshly crushed material. The vibrating pan -type conveyor has the same working principle with the feeder and uses vibrating motion to transfer material forward. The vibrating conveyor receives the material flow from the crusher and is subject to high-velocity particles which are accelerated towards the conveyor by the crusher rotor. The use of a vibrating conveyor allows the main conveyor to be located away from the path of the high-velocity particles from the crusher, while the material flow path is kept as wide and smooth as possible. Crushing plants with other crusher types, such as jaw crushers, do not include the vibrating conveyors as the crusher product does not pose a danger to the main conveyor belt.

The mobile crushing plant utilizes several belt conveyors to transfer material and increase its elevation. The conveyors utilize a reinforced rubber belt running at a velocity of roughly 2 m/s to transfer the material. Most conveyors have a straight path of material flow, but some conveyors utilize a curved structure. The conveyor belt can have a plain surface, or it can include cleats, which  are used to aid the material flow with steep conveyor angles. As the angle of the conveyor is increased, the probability of material rollback on the conveyor is increased.

Magnetic separation allows the removal of ferromagnetic material such as concrete rebar made of steel from the material stream. This is important in concrete recycling, as demolition waste often contains rebar-reinforced concrete. The mobile impactor plant considered is equipped with a cross-belt, self-cleaning magnetic separator, which utilizes its own belt conveyor to remove magnetically attracted material and to discard it from the process. The belt of the magnetic separator includes the cleats to ensure that the material picked up by the magnet is effectively removed from the magnetic field by the belt.

A vibrating screen is a component used to separate the material flow into different size fractions. The vibrating motion of a screen is typically produced by eccentric mass -based vibrators, which operate around 700 to 1000 RPM and produce a circular vibrating motion in the entire screen deck. The vibrational motion causes the material to be screened to develop a fluid-like state, in which the particle size classification becomes possible. Stratification is a process which causes the large-sized particles to reach the top of the material, allowing the smaller particles to move through the gaps, reaching the screening media. When in contact with the screening media such as a wire mesh, the particles either pass the media or continue as retained product, according to separation probability theory. (Viilo, 2011, chapter 4, p.1-26) Many of the aggregates production applications benefit from a fixed end-product maximum size, and this can be achieved by using a screen instead of only relying on the crusher setting in determining the product size distribution. Vibrating screens are used in recycling crushing applications as well for this very reason.

The product passing the screen is finished and conveyed to the final product stockpile. Screens can be configured in multiple ways, but in the case under review, a closed-loop configuration is used, as described earlier. The return path of the material utilizes two belt conveyors and one more process component, an air separator, often called “windshifter”. The windshifter applies a directed flow of air to the material flow falling from one belt conveyor to another, separating most of the lighter materials, such as plastic, insulation materials or wood, and discarding them from the return path of the process.

In addition to the main process components, the crushing plant is also equipped with a variety of different components to enable the plant to function as an independent unit. An important part of the machine is the power unit, which is an industrial diesel engine. The plant also includes different means for power transmission, such as electrical and hydraulic systems.

## 3.3 System representation and redundancy

As stated in chapter 2.1, the first step of FDD development is to obtain a priori knowledge about the system in question. This can be done in an explicit or implicit manner. The recycling crushing process is a non-stationary, dynamic process with several aspects of randomness, which makes explicit modelling of the entire process difficult. Randomness in the process is introduced mostly from the material flow and external factors such as the effects of weather. In the application of a mobile recycling crushing process, the feed material is fed into the machine commonly with an excavator. In theory, the material flow is stabilized in the feeder, but in reality, different sizes, shapes and types of feed material produce a random, intermittent material flow to the crusher. When moving forwards in the process, the material flow is stabilized and the output flow is relatively stable, but the final product flow does also include variation.

However, certain principles exist in the process, which can be modelled. Some of these principles are balancing between the boundary of explicit and implicit system representations. An example of a principle like this is that if the loading of the crusher is stabilized at a low value, the system is most likely in an idle state. If the crusher loading suddenly increases from this low, stable value, material is most likely fed into the crusher, and loadings of the different conveyors should respond in few seconds, after the material flow makes its way through the crushing plant. Similarly, crusher power draw falling to the stable low value should result in all conveyor power draws decreasing to their respective idle values as well.

The redundancy of the recycling crushing process is somewhat limited. With each of the process components consuming a significant amount of available space in the mobile mineral processing plant, it is not possible or economically feasible to implement physical redundancy in the form of additional core components. The material flow inside the machine must travel along the single path, and every component contributing to the material flow manipulation must be functioning to prevent faults in the process. Physical redundancy could be implemented in auxiliary equipment such as sensors and smaller actuators, but as the main objective of the FDD research in this system is detecting the anomalies related to the material flow, redundancy of these smaller parts of the system is left outside of the scope. Earlier in this chapter, an example was given on how the process can in some ways be modelled. This example can be linked to system redundancy as well, as control rules could be implemented based on a model like this. In the mentioned example, the conveyor power draw not increasing would indicate a problem with the process, as either the crusher would be drawing power without producing output material, or the flow of material would be blocked at some point.

# 4. CRUSHING PROCESS CHARACTERISTICS

The first research question of this thesis was set to investigate the typical process anomalies in the construction and demolition waste crushing process. Different things caused by several factors can go wrong, and the effects vary from almost unnoticeable to severe harm either to the machine itself or the process operation. In the target company, a lot of information exists on the subject, but the information is scattered among different departments and people. To answer the research question and to provide a solid background for the case study measurements, company internal interviews were used to collect information on the CDW crushing process. The focus of the interviews was on the anomalies and problems, but the normal state and typical characteristics were addressed as well.

In this chapter, the preparation, execution, and results of the interviews are covered. In the results, normal process characteristics are described first, followed by a short comparison of CDW recycling process against other crushing processes. After establishing the normal process state, interview results are combined with general knowledge of the process and its components, and common process anomalies are presented, along with their possible causes and effects on the process and machine operation.

## 4.1 Interview study

To build a solid understanding on mobile impactor crushing plant machines and the process characteristics in both normal operation and during anomalous events, a company internal interview study was planned and conducted as a part of the thesis. The goal of the interview study was to prepare for the case study measurements as well as for processing the measurement data by collecting existing knowledge about the process.

The planning of the interview study included selecting the interviewees and forming the questions. Interviews were planned to be conducted in semi-structured form, giving the interviewees freedom to introduce their views and opinions as their knowledge on the subject was broader when compared to the interviewer. However, questions were used to direct the conversation towards the subject, and to control the scope of the discussion.

Questions were planned to be broad and encourage the interviewees to bring out their own opinions on the subject. Interests in this research study could not be defined very accurately, as practically all information was valuable. The focus of the questions was on the anomalous events, and follow-up questions were asked during the interview, when an interesting topic was brought up by an interviewee. The planned questions are shown in Table 1.

***Table 1.*** *Questions for the interviews.*

| Question number | Interview question |
|---|---|
| 1 | Describe the characteristics of the CDW crushing process in its normal state. |
| 2 | How does the CDW crushing process compare to other crushing processes? |
| 3 | What are the known anomalies / problems in the CDW crushing process? How do these events differ from the normal state?[2] |
| 4 | Going through each process component, what are the problems expected to happen within the component?[3] |
| 5 | What is the most important problem in the CDW crushing process? |
| 6 | Are there any other factors that are risking the normal operation of the CDW crushing process? |

As mentioned earlier, the questions were only used to guide the discussion, and not every question was asked in every interview. During the interviews, the expertise and area of knowledge of each interviewee was considered, and the discussion was naturally focused on those topics. This approach was chosen to gather a wide range of ideas and different opinions without spending too much time on the interviews. Additionally, the durations for the interviews were limited to around 1 hour and 30 minutes, and

[2] The second part of the question was added to spark discussion on the possible sound-, vibration- and other phenomena, which could possibly be observed during the case study measurements.

[3] This question differs from number 3 to remind the interviewees not to focus on a single component only, such as the crusher. If anomalies throughout the machine were brought up by the interviewee, this question was not asked at all.

systematically going through every question would have probably resulted in narrower range of material to be collected.

The interviewees were selected by using internal knowledge in the company to determine the persons who were expected to have the most knowledge on the subject, and who were available in the given time range. Interviewee selection was defined to cover the company local factory engineering and technical support. Interviews that took place are shown in Table 2. Interviewees with the same interview number were interviewed in the same occasion, and the answers were not differentiated from each other.

***Table 2.*** *Interviewees in the study.*

| Interviewee number | Interview number | Interviewee position | Main area of expertise |
|---|---|---|---|
| 1 | 1 | Product Support Manager | Users' point of view, global outlook |
| 2 | 2 | Chief Engineer | Design aspects of mobile impactors |
| 3 | 3 | Process Owner, former Chief Engineer | Deep knowledge of the mobile impactors |
| 4 | 3 | Chief Engineer | Design aspects of mobile impactors |
| 5 | 4 | Test Engineer | Practical experience |
| 6 | 4 | Test Engineer | Practical experience |

The answers of the interviewees were collected during the interview by making notes, and by writing them up immediately after the interviews, supplementing the notes with observations. After all the interviews were completed, a single document was compiled, summarizing the key findings from the interviews. The summary included roughly seven A4 pages of text and contains a wide variety of information about the CDW crushing process and mobile impactor equipment. Furthermore, an FMEA (Failure Mode and Effects Analysis) -related approach was used to form a table of identified process failures or anomalous events. Interview results and analysis are described in the following chapters, and the relevant parts of the interview summary are shown in Appendix A.

## 4.2 Normal process characteristics

Even though the focus of the interviews was set on the anomalous events in the process, information was collected on the normal state of the process as well. Building a clear picture of the characteristics and phenomena happening in the normal process operation state helps to build the important system knowledge for initial fault detection development and the case study.

As with all mobile aggregate production processes, the general conditions of the CDW recycling crushing process can be described as harsh. Many of the process components, such as the feeder and the screen, are based on utilizing vibration, and this influences the conditions at least in vibration and audio domains. Vibrating machinery naturally produces vibrations, which are transferred to the steel frame of the plant and other components, interfering with each other. Other types of vibration sources are also present all over the process and the machine. The feed material is dropped onto the feed hopper from variable height, delivering impact-type loads to the feeder, vibrating the entire plant structure. The working principle of the crusher relies on using the energy of feed material impacts to crush the larger particles, producing very different types of vibration depending on the feed material. Noise is also generated by different phenomena across the process. Some of the energy from rock impacts and material flow in general is transferred to audible sound, and some components of the process, such as the vibrating conveyor and the screen produce considerable noise even without material. The power unit of the mobile crushing plant cannot be left out either, as the diesel engine exhaust noise and noise produced by the powerful cooling fan of the engine are significant as well. With the machine operators having to rely on hearing protection, sound produced by different parts of the process is typically loud. In addition to noise and vibration, dust increases the harshness of the process as well. Dust is produced from crushing the feed material, and material handling causes the existing dust to become airborne. The level of dust particle concentration depends greatly on the application. In general, the harsh conditions are caused by a combination of different factors and must be considered when working with the process with FDD development not being an exception.

As a part of the system knowledge, variability of the process is an important factor to acknowledge when discussing process fault detection. According to the interview study, main contributing factors introducing variability in the process are the feed material and operator actions.

Demolition waste, the feed material of the process, cannot be strictly defined, as it contains different types of material in different ratios from application to another. The building or structure that has been demolished greatly affects the composition of the CDW. The interviewees described the feed material composition with different terms, but the main consensus was that the feed material can include virtually anything. Some of the interviewees brought up that the feed material can be relatively “good” in some applications, referring to the absence of any especially problematic components, but it is very possible that in the next application the plant is fed with very miscellaneous material. In the ideal situation, demolition waste consists of reasonable-sized concrete chunks, with the reinforcing rebar pieces cut to under 1 meter in length. As stated by the interviewees, this is often not the reality, and the plants are fed with oversized chunks of concrete and steel reinforcements or structures. Other foreign objects include other metallic materials along with the expected concrete rebar, electric cables or wires, structural steel wires and a variety of lighter materials such as pieces of tarpaulin. According to the interviewees, the base material can also be different from concrete, such as material mostly containing bricks and glass. These materials are lighter and easier to crush, even to a point of lowering the power draw of the crusher dramatically from typical crushing process power draw.

These factors result in a scale of different feed material compositions with varying properties. The hardness and toughness of the base material, proportion of metallic, non-crushable materials, proportion of light materials, feed material size distribution and even the moisture content of the feed material are significant factors affecting in the state of the crushing process in general. Tougher material requires more energy to be crushed, increasing the power consumption of the crusher. Different feed material size distributions produce different conditions in terms of material bypassing the crusher, the power draw and operation of the crusher, and the operation of the screen and return conveyors. The amount and quality of steel rebar and other foreign objects directly affects the frequency of problems caused by these objects.

In addition to high variability in the feed material, the operators of the crushing plant were stated as being significant sources of non-stationarity in the recycling crushing process. The automation system of the crushing plant controls the operation of different components in the plant, but the operator still has a large role in running the process. The decisions of the operator include the configuration of the machine, pre-processing and manual manipulation of the feed material, rate of feeding the machine, along with other factors as well, such as special measures to prevent a certain problem.

The configuration of the crushing plant can differ from application to another. According to the interviewees, most recycling crushing applications utilize a vibrating screen to produce end-product with calibrated size distribution, but the machines can also be operated without the screen and therefore in an open-loop configuration. The type and size of the screening media are also configurable by the plant operators. In addition to the main vibrating screen, the preliminary screening part of the vibrating feeder can be equipped with different screening media, or even be completely blocked, resulting in different process conditions in terms of the material flow bypassing the crusher. In the interviews, an example case of this was discussed. Crusher bypass is also affected by the decision whether the conveyor for fine fraction is used or not. The setting of the crusher also affects the process state, as it has a direct effect on the size distribution of the material, especially between the crusher and the screen, and on the return conveyors. Use of the airflow-based light fraction separator removes light materials from the return flow, and if the separator is not used, light uncrushable materials may build up on the closed loop. Configuration of the machine can also change because of a failure, wear, or some operational phenomena in some of the process components. For example, a worn conveyor belt or build-up of sticky material can cause the process state to change.

Operator behaviour can also be connected to the feed material causing variability in the process. Plant operators can manually manipulate or discard some of the feed material, if they estimate it being problematic. Operators can also supply the feed material cautiously, for example when assessing that the risk for material flow obstruction is high. By feeding the plant intermittently, operators can ensure that there are no blockages or other problems before continuing with the feeding process. A major enabling factor for these actions is that the mobile impactor crushing plant is often being fed by an excavator from a stockpile, rather than being fed by the product conveyor of another machine.

With the mobile impactor crushing plants operating in an outdoor environment, the environmental factors are also significant. The ambient temperature and relative humidity influence several components and phenomena. Low temperatures can cause stiffness in conveyor belts and increased hydraulic fluid viscosity, while high temperature increases the need of cooling, for example increasing the noise and airflow of the power unit cooling fan. High relative humidity in the cold and other weather phenomena can contribute to the development of environmental conditions, where ice is formed in the structures, or the moisture in the feed material causes it to freeze and build up on the structures of the plant. In above-freezing temperatures, rain increases the feed material moisture content, which can cause the material to stick to plant structures.

It can be concluded that the demolition waste crushing process is far from stationary, even when operating in normal conditions. An expected process state does not exist as the operator actions, variations in feed material and different environmental conditions introduce variability in the process. According to the interviewees, even the normal state of the demolition waste crushing process is interrupted relatively often, with interruptions happening on an hourly basis.

## 4.3 Comparison to other crushing processes

Many different crushing processes exist to produce different sized aggregates, reduce the size of ore in mining applications or enable the recycling of materials such as slag. Different crusher types are used for different needs and the auxiliary equipment are arranged to suit the needs of a particular application.

Some crushing processes take place in stationary plants. Stationary crushing processes are built in locations with a continuous need for material size reduction and larger scale operations. When comparing the mobile CDW crushing process to any stationary process, the sources for variation are much more pronounced in the mobile applications. The basic principle of mobile crushing plants is the ability to move the plant quickly from one location (and feed material) to another, which introduces several variation sources.

Even among the mobile crushing plants, the demolition waste crushing process stands out as a special case. Regular aggregate production processes might be designed for producing an end product of certain type from similar feed material, and therefore be run in relatively stable conditions. Even if the feed material or other process parameters are changed, the change might be less dramatic than a switch from one demolition waste type to another, and in regular aggregate production processes the feed material does not include a variety of unexpected and challenging objects and materials. Regular rock crushing processes have also been established to function with a low frequency of interruptions during decades of development and can be said to be more reliable than the newer demolition waste crushing process.

As stated by the interviewees, other recycling processes, such as asphalt crushing, can be relatively similar to the CDW crushing process. However, it was also stated that the problems are often process-specific, as for example the recycling crushing process for asphalt comes with its own challenges.

Overall, the mobile demolition waste crushing process can be said to be among, if not the most challenging of different common crushing processes. The feed material is very heterogenic and varies greatly from one site to another. The mobility of the crushing plant introduces its own challenges, and events that would be classified as unexpected in other processes, become expected and everyday occurrences when the demolition waste crushing process is considered.

## 4.4 Common anomaly types and phenomena

As concluded, the CDW crushing process is variable and non-stationary, with several factors contributing to the changing conditions. Feed material can greatly differ from application to another, and different machine configurations, ways of operating the machine and environmental conditions ensure that finding similar applications is rare. From this, an assumption is made that the anomalous events also vary from application to another, and very different failure modes for the process exist.

In the interview study, focus was set on the anomalous events in the CDW crushing process. While the detailed opinions of the interviewees differed from each other, a clear and common consensus was that pre-processing of the feed material is one of, if not the most important thing in preventing process anomalies and affecting their quality and quantity. This means that the crushing plant is fed with reasonable-sized material, and that for example the rebar pieces in the feed material have been cut to short enough length.

The anomalous events discovered in the interview study were collected to a table, after which they were analysed. The goal was to build a solid background on the subject, and to answer the research question addressing the possible CDW recycling crushing process anomalies. The information from the interviews was condensed down to a total of 11 identified anomalous events which have different causes and effects on the crushing plant operation. The collected anomalous events are shown in Table 3.

*Table 3. Identified CDW crushing process anomalies and involved components.*

| | Identified problem | Involved component(s) |
|---|---|---|
| 1 | Pile-up of rebar / similar objects inside the machine | Crusher, lower pan feeder, main conveyor, magnetic separator |
| 2 | Rebar jammed in conveyor structure | Main conveyor, rest of the process |
| 3 | Product conveyor overload from sudden increase of fine fraction | Product conveyor |
| 4 | Feeder blocked by rebar / similar object | Feeder / pre-screen |
| 5 | Vibrating screen media clogged | Screen |
| 6 | Large metal objects stuck to magnetic separator | Magnetic separator |
| 7 | Main conveyor speed decreased[4] | Main conveyor |
| 8 | Bypass chute blocked | Bypass chute |
| 9 | Breaker plate jammed in withdrawn position | Crusher, return conveyors |
| 10 | Rebar / cable wrapped around the rotor | Crusher |
| 11 | Loose parts in vibrating components | Feeder, lower pan feeder, vibrating screen |

As can be seen from the table, rebar or other non-crushable objects account for several process failure modes. From the interview results it can be concluded that rebar getting jammed in different parts of the machine can cause anomalies all over the process and the machine. Otherwise, the variety of different problems is wide, and many of the process components are involved. As the identified anomalies are spread both in terms of anomaly type and physical location, no clear areas of focus can be formed.

[4] Only applies to machines with a hydraulically driven main conveyor.

## 4.5 Reasons for process malfunctions

After establishing the most common identified anomalous events in the CDW crushing process, the possible causes of the faults were analysed. Some of the information used in the analysis was collected from the interviews, and general knowledge of the process and mobile crushing plants was used to estimate the direct causes for each process anomaly. The causes for each process anomaly are shown in Table 4.

***Table 4.*** *Possible causes for identified anomalies.*

| | **Identified problem** | **Possible cause(s)** |
|---|---|---|
| 1 | Pile-up of rebar / similar inside the machine | Rebar pieces get tangled to each other, forming a "ball", which is jammed under the power unit or near the magnetic separator |
| 2 | Rebar jammed in conveyor structure | Rebar pieces randomly end up in the rollers or structure of the conveyor |
| 3 | Product conveyor overload from sudden increase of fine fraction | Large fraction of fines in the feed material |
| 4 | Feeder blocked by rebar / similar | Shape of steel pieces results in them getting stuck in the feeder / pre-screen |
| 5 | Vibrating screen media clogged | Shape of certain pieces within the material flow results in them getting stuck on the screening media |
| 6 | Large metal objects stuck to magnetic separator | Heavy metal objects are pulled towards the magnetic separator with a great force |
| 7 | Main conveyor speed decreased | Conveyor is overloaded with heavy material flow |
| 8 | Bypass chute blocked | Rebar / other steel pieces get jammed in the bypass chute |
| 9 | Breaker plate jammed in withdrawn position | Cause unknown |

| | Identified problem | Possible cause(s) |
|---|---|---|
| 10 | Rebar / cable wrapped around the rotor | Long uncrushable objects get bent and eventually wrapped around the crusher rotor |
| 11 | Loose parts in vibrating components | Normal operation can cause parts to become loose |

Causes shown here aim to assess the different process phenomena, which are directly responsible for any given anomalous event. The estimated causes strive for answering the question **how** an anomaly happens and help in building the overall picture on the failure modes of the process.

After the possible causes were assessed, the event chain leading to anomalous events was analysed in the form of root cause analysis, again to build understanding on the events. With the root causes, the question of **why** a given problem occurs, is pondered. The root causes for each identified problem are shown in Table 5.

***Table 5.*** *Derived root causes for identified process anomalies.*

| | Identified problem | Derived root cause(s) |
|---|---|---|
| 1 | Pile-up of rebar / similar inside the machine | Rebar in feed material, not enough space above the conveyors |
| 2 | Rebar jammed in conveyor structure | Rebar in feed material, conveyor structure not protected well enough, area above conveyor not smooth enough |
| 3 | Product conveyor overload from sudden increase of fine fraction | Plant is fed with material that has a high percentage of fines |
| 4 | Feeder blocked by rebar / similar | Feeder / pre-screen structure not optimal for bypassing fines and not collecting metal objects, rebar in feed material |
| 5 | Vibrating screen media clogged | Some of the feed material is not crushed and cannot be picked up by the magnetic separator, ending up on the screen deck and clogging it |

| | Identified problem | Derived root cause(s) |
|---|---|---|
| 6 | Large metal objects stuck to magnetic separator | Plant is fed with too large and heavy metallic objects; magnetic separator is not designed for such loads |
| 7 | Main conveyor speed decreased | Plant is fed with material that does not load the crusher enough to limit the capacity, overloading the conveyor |
| 8 | Bypass chute blocked | Pre-screen design allows the metallic objects to enter the bypass chute, bypass chute design promotes objects getting jammed (converging?) |
| 9 | Breaker plate jammed in withdrawn position | Crusher is overloaded with tough feed material, causing the breaker plate to be forced to the withdrawn position |
| 10 | Rebar / cable wrapped around the rotor | Plant is fed with out-of-specification feed material (too long rebar / wire / cable) |
| 11 | Loose parts in vibrating components | Vibration exposes different joints to disassembling themselves or materials to failure due to fatigue |

Most of the derived root causes are somehow connected to the feed material, and the importance of pre-processing the feed material, and operator responsibility is even further strengthened by the root cause analysis results. According to the estimated root causes, feeding the plant with material it is not designed to handle is the root cause of most of the identified anomalies.

When assessing the results, a question on the design principles of the plant is naturally raised. If the mobile crushing plant is designed for CDW recycling processes, it should be able to handle the typical feed material without developing blockages or other anomalies in the process. However, designing a machine that fulfils all the other requirements while being able to handle the most difficult feed material is definitely not an easy task. According to the root causes derived from the interview results, future design considerations should include ensuring that the path of the material flow is as smooth as possible and has enough space for larger-than-expected objects. According to the interviewees, this has been the development path in the history, but the importance of such design principles is still high.

## 4.6 Effects on the machine operation

Different process anomalies have a different effect on the operation of the mobile crushing plant. The effects on the machine operation were analysed in a similar way to the causes and are shown in Table 6.

To assess the severity of each identified anomaly, a severity rating was assigned on a 3-point scale (Mild – Moderate - Severe). If the identified fault is of a cumulative type, this is mentioned as well. The ratings from mild to severe are established to illustrate how different anomalies have different consequences and require different actions to resolve. A mild anomaly does not necessarily require halting the production immediately, and it might eventually clear itself, or on the other hand develop into a worse problem. Moderate anomalies require the production to be halted temporarily and actions to be taken, but the machine is not damaged, and manual work required to resolve the event is not very big. Severe anomalies either involve serious damage to the machine, significant loss of production time and require repairs or manual work, such as clearing up a machine blockage to be conducted. According to the interviewees, a severely blocked mobile crushing plant takes somewhere around 8 hours of manual labour to clear up, which is an extremely unwanted scenario.

As expected, the wide variety of different anomalous events can lead to very different effects on the machine operation, and effects vary from total blockage of the machine to very little disturbance in the operation of the plant. Some of the anomalous events include damage to the machine, and some can be very easily resolved. The worst anomaly types possess a risk for total blockage of the machine, and every possible action should be taken to minimize the risk for these anomaly types in every stage of the machine design.

***Table 6.*** *Estimated effects of anomalies on the crushing plant operation*

| | Identified problem | Effect(s) | Severity |
|---|---|---|---|
| 1 | Pile-up of rebar / similar inside the machine | Obstruction of material flow, total blockage of the entire machine | Severe |
| 2 | Rebar jammed in conveyor structure | Possible damage to the conveyor belt | Moderate / severe |
| 3 | Product conveyor overload from sudden increase of fine fraction | Conveyor possibly slowing down as a result of overload | Mild, severe if persistent |
| 4 | Feeder blocked by rebar / similar | Decreased performance of the pre-screen and in bad cases the feeder | Mild, cumulative |
| 5 | Vibrating screen media clogged | Decreased performance of the vibrating screen | Mild, cumulative |
| 6 | Large metal objects stuck to magnetic separator | Magnetic separator discharge belt stops moving if the magnetic force pulling on the metal object generates too much friction for the belt | Moderate |
| 7 | Main conveyor speed decreased | Total blockage of the entire machine if material flow not reduced | Mild, severe if persistent |
| 8 | Bypass chute blocked | Fine material not bypassed if the chute is completely blocked → decreased production and unnecessary crusher load / energy consumption | Moderate |
| 9 | Breaker plate jammed in withdrawn position | Oversized material is passed through the crusher → can cause blockages in return conveyors and possibly decrease product quality | Moderate |
| 10 | Rebar / cable wrapped around the rotor | Reduced performance if happens in excess. In small quantities not very harmful | Mild |
| 11 | Loose parts in vibrating components | Reduced performance or equipment damage | Moderate, cumulative |

# 5. MEASUREMENT PLANNING AND IMPLEMENTATION

To perform the case study for evaluating the feasibility of monitoring the construction and demolition waste crushing process, a measurement period was conducted in a real-world application on a customer site.

This chapter presents the measurement implementation and application as well as describes the workflow of conducting the data collection from the field. The scope of the measurements extends beyond the scope of this thesis, and designing the measurements is a subject of its own. Therefore, the design process for the measurement period is not discussed in-depth in this document.

## 5.1 Measurement planning and objectives

The CDW crushing process and crushing processes in general involve a variety of components and equipment. Even when the subject is narrowed down to the scope of this thesis, a mobile impactor crushing plant, the system in question is a complex machine with different subsystems working together to fulfil the requirements of a given material processing task.

As discussed in the chapter 4, the variety of possible anomalies and problems is also wide. Any of the process components cannot explicitly be stated to be “problem-free”, and due to the unpredictable nature of the process, even determining the most common anomalies is a difficult task, greatly depending on the application-specific factors.

As a result, planning the first measurement setup for process monitoring research cannot be easily reasoned. For the measurement period planning, common knowledge of typical applications and educated guesses were used to determine the required sensors and other measurement setup. The results presented in the chapter 4 were also referenced to estimate the most potential parts of the process for anomaly occurrence. The unpredictable nature of the problematic components was addressed by aiming to build the measurement setup to cover as much of the process as possible, given the limitations in available measurement hardware, budget, and other general factors, such as schedule, and the fact that the measurement period was conducted on a customer site. Actions on the site had to be arranged not to cause excessive machine downtime or disturb the operation of the machine.

The measurement period included many different objectives, with some of them addressing the requirements of the research in this thesis, while others included data collection for different research interests as well. The main objective concerning this thesis was to record CDW crushing process anomalies using several different data types.

In the early planning of the measurements, it was decided that the measurements would be implemented as continuous. In practice, this means that no trigger conditions would be established, and the hardware would be running and collecting data continuously regardless of the process state or any other factors. As a natural consequence, this results in a relatively large amount of normal process data being captured. Triggering of the measurements was evaluated as being problematic due to the nature of some process anomalies. As described in chapter 4.4, even the identified process anomalies include events which do not necessarily have immediate effects, which build up over time, or which cannot be observed by operators or other personnel working in the proximity of the machine. Therefore, it was evaluated that no reliable trigger condition would exist in the measured signals or anywhere else in the machine. Manual triggering would also have been challenging due to the same reasons. Additionally, manual triggering would have required some form of interaction with the measurement setup, which would not necessarily have been realizable given the limitations mentioned earlier.

The decision of implementing the measurements as continuous raised the need for identifying the regions of interest from the continuous measurement data. As the variety of possible process anomalies was estimated as being large and the objective of the research was to investigate the possibility of automatic anomaly detection, it was clear that the state of the machine and the process had to be manually observed throughout the measurement period. The plan was to conduct the measurements in a way that when the measurement hardware is running, a person is continuously observing the process and making notes of the process and machine state, as well as other observations on factors that might influence the results of the study. Observations were designed to be incorporated with the actual measurement data in the later phase, requiring accurate time synchronization between the data collection and manual observations.

After the fundamental idea of the measurement period was established, measurement targets were selected. Different research interests affected the decisions for the quantities being measured, but the focus was to support the process monitoring study. A wide range of different measured quantities was chosen, as arranging a measurement case always requires preparation work, and using the available hardware, it was relatively easy to add different quantities.

In the planning phase, the research interests covered three categories, which are:

1. Mechanical quantities and existing control system data,
2. Audio and
3. Acceleration.

The first category includes process-related data already available on the CAN bus of the machine, as well as other mechanical quantities, such as conveyor power draw. The purpose of the category is to capture the state of the process components in the plant in the form of data that can be measured directly, and which mostly already exists in the automation bus. Measured quantities selected for this category are shown in Table 7.

***Table 7.*** *Measured mechanical quantities.*

| Number | Quantity | Data source |
|---|---|---|
| 1 | Product conveyor hydraulic pressure | CAN bus |
| 2 | Crusher power | CAN bus |
| 3 | Crusher power target | CAN bus |
| 4 | Crusher speed | CAN bus |
| 5 | Hydraulic pump 1 pressure | CAN bus |
| 6 | Hydraulic pump 2 pressure | CAN bus |
| 7 | Feeder control percentage | CAN bus |
| 8 | Diesel engine RPM | CAN bus |
| 9 | Diesel engine load percentage | CAN bus |
| 10 | Product conveyor belt velocity | CAN bus |
| 11 | Hydraulic oil temperature | CAN bus |
| 12 | Diesel engine coolant temperature | CAN bus |
| 13 | Engine charge air temperature | CAN bus |
| 14 | Engine cooler fan control value | CAN bus |
| 15 | Main conveyor electric power | Power transducer |
| 16 | Vibrating conveyor hydraulic pressure | Pressure sensor |
| 17 | Return conveyor hydraulic pressure | Pressure sensor |

Illustrative locations of the location-specific quantities are shown in Figure 6. The shown locations describe the location of the physical phenomena, sensor locations were different to the ones shown.


*Figure 6.* Locations of physical measured quantities (Modified from: Viilo, 2011)

Audio category consisted of process sound measurements. Three audio channels were selected to be used, and the microphone locations were chosen to include most of the process, with research interests outside of this study as well. Audio measurement channels are shown in Table 8.

*Table 8.* Channels and sensor locations for audio measurement

| Channel | Sensor location |
|---|---|
| Microphone 1 | Magnetic separator |
| Microphone 2 | Light mast |
| Microphone 3 | Vibrating conveyor / by-pass chute |

Microphone locations are shown in Figure 7.

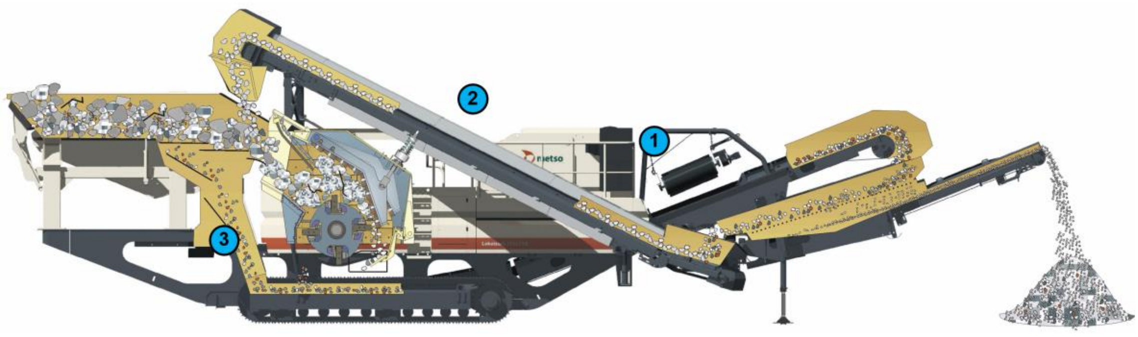


*Figure 7.* *Microphone measurement locations (Modified from: Viilo, 2011)*

In the acceleration category, simple acceleration measurements were included. Acceleration data was measured to supplement other measurements, and on the other hand was not planned to comprehensively cover the entire process. Vibration channels are shown in Table 9.

*Table 9.* *Channels and sensor locations for acceleration measurement*

| Channel | Sensor location |
|---|---|
| Acceleration 1 | Main conveyor frame |
| Acceleration 2 | Magnetic separator frame |
| Acceleration 3 | Machine main frame |

Accelerometer locations are shown in Figure 8.

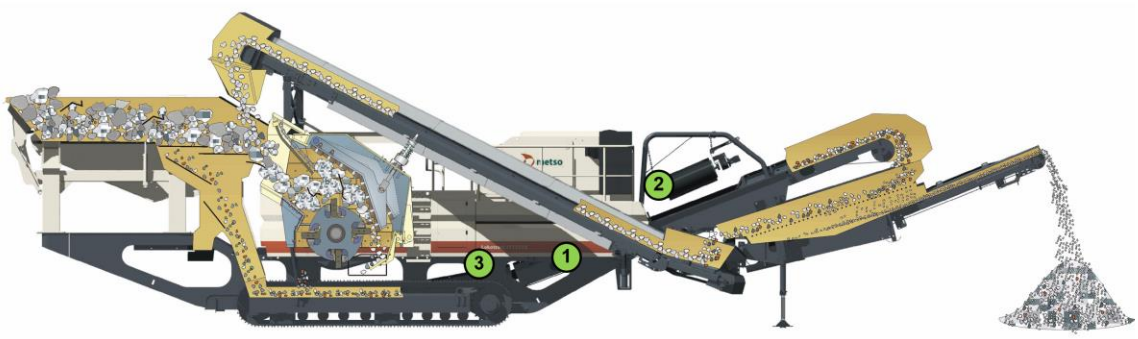


*Figure 8.* *Acceleration sensor locations (Modified from: Viilo, 2011)*

## 5.2 Description of the application

As mentioned in the chapter 4.2, crushing processes in general, including CDW recycling crushing process, have a large amount of variation. Recycling crushing processes especially can be very different from one another, and the biggest factors in defining the process are feed material and final product from the crusher.

Before the measurement period, requirements were set to define a suitable process for the task of investigating the feasibility of process monitoring and anomaly detection. The scope was limited to CDW crushing processes, which can be stated to be the most vulnerable in terms of process anomalies. Requirements included the use of an available crushing plant, and a suitable mobile impactor crushing and screening plant was selected to be used in the measurements. The individual machine used in the measurements is a prototype machine, having several differences compared to a serial production unit. With the machine being selected, available applications were narrowed down to the applications of the plant in question, and the first suitable application was selected. Suitability of the application was evaluated based on expertise and experience of typical CDW crushing processes inside the company.

The selected application was a demolition site of a school building. Previously, the school building was demolished with an excavator and other required machinery, and the demolition waste was temporarily stored in a stockpile. A contractor was responsible of using the mentioned mobile impactor crushing and screening plant to process the entire former school building, crushing the feed material to an output size distribution of 0 – 90 mm. The crushing was performed in a single phase, meaning that the machine in question was the only piece of crushing and screening equipment in contact with the material, and no secondary- or tertiary crushing phases or external screening equipment were used. In the Figure 9, the crushing plant is shown on the measurement site.


***Figure 9.*** *The mobile crushing plant used in the measurements. The feeder is located on the right and material flows from right to left.*

The operation of the plant was carried out in a typical way. The contractor used an excavator for feeding the plant from the stockpile, and a wheel loader to relocate the product from the product stockpile to a larger one. As the work progressed, the plant was periodically track-driven towards the shrinking feed stockpile. The contractor was an experienced demolition service provider and operated the plant professionally. Special care was paid to feeding the plant, as the excavator operator wanted to prevent objects that could cause damage from entering the crusher. It was known that the feed material stockpile included very large natural stones, and as a special mention, large steel counterbalance weights from the lifts of the demolished building.

Feed material plays an important role of forming the typical characteristics of a crushing process. In this application, the feed material presented a one example of construction and demolition waste from a Finnish school building. The feed material could be described as easy for the crusher, as the crusher power draw was evaluated to be relatively low. The proportion of fine material was high, which on its own can result in low crusher power draw. In addition to the fine fraction, the feed material was composed of bricks, different sized pieces of concrete and different sized natural stones, containing also different types of uncrushable material, such as different sized rebar pieces, wood pieces, lengths of electric wire and small amounts of other materials. Defining an accurate size distribution for the feed material would have required tests, and a more extensive evaluation of the feed material quality is therefore passed in this context.

Illustration of the demolition waste used as the feed material in the measurement application is shown in Figure 10 and Figure 11.

***Figure 10.*** *Demolition waste used as feed material, size 10 glove for rough size reference.*

***Figure 11.*** *Feed material included different rocks, concrete, bricks, and other materials.*

The mobile crushing plant can be configured in multiple ways for different applications and needs. In this application, the contractor responsible for crusher operation had decided not to use the side conveyor of the crushing plant. With the side conveyor being disabled, fine material passing through the pre-screen was directed to bypass the crusher and forwarded towards the later stages of the process with the crusher product. Other configuration choices of the plant included using the plant in closed-loop mode by having a screening media in use. The screening media used was a 110 mm wire mesh, directing oversized material to the return conveyor and eventually back in the crusher.

Output of the crushing plant could be divided to three parts. The main output material flow is naturally the crushed aggregate. The product in this application was described with the size distribution of 0 to 90 mm. With the feed material including different types of uncrushables, two different by-product streams are produced as well.

The more significant by-product stream is separated from the material flow by the magnetic separator. Consisting of rebar and other forms of ferromagnetic materials, this stream is discharged out of the side of the crushing plant, and in this application, collected to a portable open steel container, which is emptied periodically by the machine operator crew. The amount of separated metal required the container to be emptied several times during a typical working day. An illustration of the metallic material by-product stream is shown in Figure 12.

***Figure 12.*** *Metallic by-product stream separated by the magnetic separator.*

Another by-product stream is produced by the so-called “Windshifter”, an airflow-based light fraction separator located in the material flow to the return conveyor on the side of the plant opposite to the magnetic separator discharge. The contents of this by-product stream included wood pieces, electric wire, insulation materials and other relatively light objects which were not passed through the screening media. An example of this by-product stream is shown in Figure 13. This stream was also collected in an open steel container, similar to the one used with ferromagnetic by-product stream.

***Figure 13.*** *Light fraction by-product stream from the windshifter*

As practically every demolition site differs from one another in terms of feed material and other conditions, evaluating the typicality of the site is not straight-forward. The application in question represented an example of a Finnish demolition waste recycling contract, and there were no clear factors making the application stand out from a typical CDW crushing application. Possibly the most notable factor was the rather big proportion of fine material in the feed, and the feed material being generally easy to crush. An example of a different process could have the feed material include less fines, more and larger chunks of concrete and less bricks. The chunks of concrete could possibly also include more rebar strongly embedded in them, causing a less perfect separation of metallic materials from the crushables. This typical characteristic of concrete recycling processes was missing on the measurement application.

## 5.3 Measurement hardware

To collect multi-domain process data from a mobile crushing and screening plant, several components of measurement hardware are required. Information from only the CAN bus of the plant can be recorded relatively easily, but as the goal of the measurements was to utilize different domains for data collection, a more advanced system was required.

In this sub-chapter, the measurement hardware used is described, ranging from the main component, the data acquisition system, to the sensors and other hardware used to collect the different types of data. Selection of the measurement hardware was mainly done by utilizing measurement hardware already available in the company. For the microphones, a short description of the sensor selection process is included, as they were specifically ordered for this project.

### 5.3.1 Data acquisition hardware

The core of the entire data collection system was a modular *Q.brixx XL* data acquisition (DAQ) system made by *Gantner Instruments*. The system includes a modular structure, which allows customization of the DAQ unit for different needs. In the modular structure, one module is a controller, providing interfaces for system configuration, data storage and other system-wide needs, while actual sensors are connected to different measurement modules. A wide selection of measurement modules is available, including different general-purpose modules, acceleration modules, special strain gage modules and many others. (Gantner Instruments, 2023)

The configuration used for the measurements was available in the company and was suitable for the measurements without major changes. To ensure the measurement hardware performance with high sample rates, measurement module data buses were reviewed and set according to manufacturer recommendations. The software configuration of the DAQ system was also reviewed and set according to recommendations before the measurement period. These actions were made, because the DAQ system was previously known not to perform optimally with high sample rates before the physical and software configuration changes were made. General structure of the modular system with individual modules is shown in Table 10.

***Table 10.*** *Data acquisition system modules*

| Module function | Model |
|---|---|
| Controller, interface | Q.brixx-X station T |
| IEPE sensor module (microphones) | Q.brixx-XL A111 BNC |
| IEPE sensor module (accelerometers) | Q.brixx-XL A111 BNC |
| General purpose analog measurement | Q.brixx-XL A107 |
| General purpose analog measurement | Q.brixx-XL A108 |
| General purpose analog measurement | Q.brixx-XL A108 |

The modular DAQ hardware during planning phase testing is shown in Figure 14. The first module from the top is the controller module, and modules are in the order of Table 10.

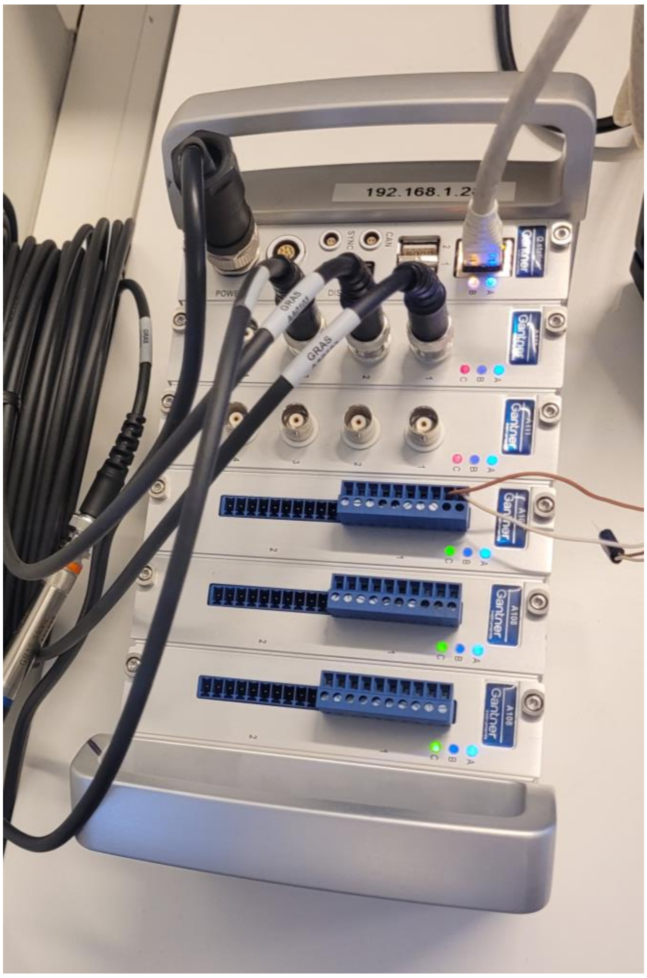


***Figure 14.*** *Gantner Instruments data acquisition system used in the measurements during office environment testing.*

With the presented configuration of the modular DAQ system, connecting all the required sensors was possible. Additionally, the CAN bus of the plant could be connected to the controller module of the system, enabling the recording of the defined signals in the CAN bus. Powering the system was also possible by connecting the DAQ system to the 24 V DC power available in the crushing plant.

The DAQ system offers a variety of possibilities for storing the measured data, and in this case, a USB memory stick was used. After each measurement day, the files were transferred from the mass storage media to a computer.

The data acquisition system supports sample rates up to 100 kHz with the IEPE measurement modules. Sample rates were chosen for each measurement quantity group, and the selection was based on experience from other measurements. A sample rate of 40 000 Hz was selected for the audio signals, enabling analysis in the frequency domain up to 20 kHz. For the accelerometers a sample rate of 10 000 Hz was used, and for all the other quantities, a sample rate of 500 Hz was selected. The signals collected from the CAN bus were updating noticeably slower than the selected sample rate and were therefore repeated in the raw data between their respective updates by the DAQ system.

### 5.3.2 Microphones

One of the interests for the measurement period was to record the sound of the process from different points. Several options exist for audio recording, but for example using individual recorders would have been challenging. Therefore, a requirement was set in the planning phase of the measurements, that the existing DAQ system should be used for audio recording. Using the data acquisition system to record the audio data would result in the audio data automatically being time-synchronized with all the other measurements and would open the possibility for using the audio data to calculate sound pressure levels of each microphone location.

The existing data acquisition system supported the use of IEPE -type sensors with BNC-type connectors. This condition rendered IEPE-compatible measurement microphones as a suitable sensor type for the audio measurements. As no such hardware was available in the company, possible options were reviewed, and a suitable model was selected. The selected measurement microphone model was 146AE constant current power free-field measurement microphone made by GRAS. The 146AE microphone was selected after comparing the specifications of few available options. The most important criterion for the microphone selection was the resistance to rough environmental conditions, such as low temperature, dust, water and vibrations or shocks. However, good overall quality was also required to capture accurate data for different uses. The specifications of the selected microphone model are shown in Table 11.

*Table 11. GRAS 146AE Microphone specifications*

| Property | Value |
|---|---|
| Frequency range | 3,15 Hz – 20 kHz (± 2 dB) |
| Sensitivity | 50 mV / Pa |
| Dynamic range | 18 dB(A) – 133 dB |
| Response | Free field |
| IP rating | IP 67 |

### 5.3.3 Accelerometers

Collecting vibration data from the process has several uses, and collecting some vibration data was included in the research interests in this work as well. For vibration sensors, 622A01 accelerometers made by IMI sensors were used. Specifications of the accelerometers are shown in Table 12.

*Table 12. IMI Sensors 622A01 Accelerometer specifications*

| Property | Value |
|---|---|
| Frequency range | 0,58 Hz – 4000 Hz |
| Sensitivity | 100 mV / G |
| Resonant frequency | 20 kHz |
| Type | Piezoelectric |
| IP rating | IP 68 |
| Mounting | Magnetic |

### 5.3.4 Other hardware

In addition to microphones and accelerometers, other sensor types were used to complement the data available from the CAN bus of the plant as well.

For the measurement of the main conveyor power, a *Carlo Gavazzi CPT-DIN "Advanced version"* electrical power transducer was used. The power transducer measures the power draw of the conveyor driven by 3-phase induction motors by calculating the AC power from voltages and currents of the motor. The power transducer was mounted in an electrical cabinet of the crushing plant and the signal was fed to the DAQ system as a standard 4 – 20 mA current signal. The power transducer is shown in Figure 15.

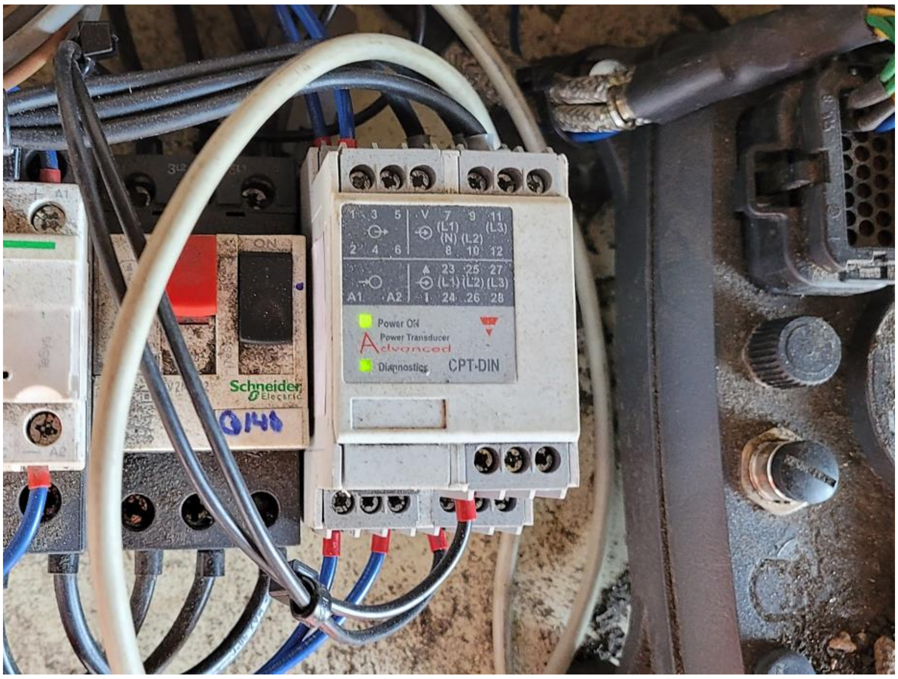


***Figure 15.*** *Carlo Gavazzi CPT-DIN power transducer installed in the crushing plant.*

To measure the hydraulic pressures, 600 bar pressure sensors were used. Hydraulic pressures were measured near the main hydraulic manifold of the crushing plant, as test couplings were conveniently available in the actuator pressure lines near the manifold. With this arrangement, pressure losses in the hydraulic lines are not considered, but the goal of the measurements was to mainly monitor the change in pressure values and did not require the absolutely correct actuator pressure values to be recorded. Thereby, performing the measurements from the manifold was stated to be sufficient. The return conveyor hydraulic pressure sensor is shown in Figure 16.

***Figure 16.*** *Pressure sensor on the return conveyor pressure line*

To ensure that the measurement period was well documented in terms of the process, two cameras were included in the measurement setup. After a review of options, GoPro HERO 9 Black -model action cameras were chosen to be mounted on the crushing plant.

## 5.4 Implementation of the field measurements

After the measurement planning and hardware selection, the equipment described in the previous chapter was installed on the crushing plant. In this sub-chapter, the hardware installation and actual measurement period is described.

### 5.4.1 Hardware installation

At the time of the initial phase of this work, the target of the measurements, a mobile crushing plant (Metso Lokotrack® LT1213SE™), was under a scheduled modification round at the target company factory. As the round was nearing completion and the first application of the machine was confirmed to suit the needs of this study, the measurement hardware was installed on the plant. By performing the installation at the factory, process downtime caused by the measurements was minimized.

The core component of the measurement hardware, the DAQ system, was mounted to the side of the crushing plant inside a suitable electric cabinet. The cabinet protected the data acquisition equipment and necessary electrical connections. For instance, a 24 V DC rail was established to provide electrical power from the crushing plant to the DAQ hardware, pressure sensors and the cameras used. The cabinet mounted on the plant is shown in Figure 17.

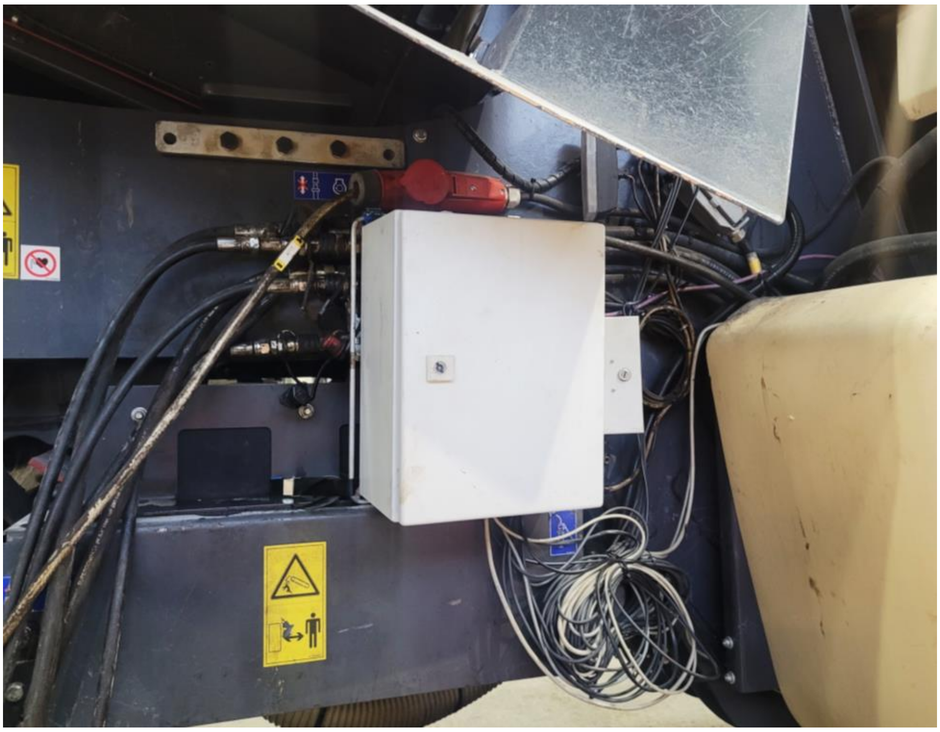

***Figure 17.*** *Electric cabinet for the data acquisition hardware mounted on the side of the crushing plant.*

After mounting the electric cabinet, wires for sensors and other needs were installed on the machine. The CAN bus of the machine was accessed from an electric cabinet of the plant by connecting a custom-made cable between the main user interface module of the plant and its connection to the bus, providing the CAN H and CAN L wires to be connected to the DAQ hardware. The main conveyor power transducer signal was also accessed from the same electric cabinet. A cable for these was installed between the two electric cabinets and connections were made to enable data logging. Connection to the 24 V DC power was made by installing a special cable on the machine, connecting to a 24 V outlet on the operating panel of the crushing plant and delivering the power to the DAQ cabinet. Acceleration-, microphone-, and pressure sensor cables were installed on the plant and connected to the data logger.

After installing the cables, sensors were added to the locations shown in chapter 5.1. Most of the sensors were installed at the factory and installations were finished at the measurement site. Uniaxial accelerometers were mounted to their locations with their magnetic bases, and all three locations provided a good, flat surface for the magnetic sensor attachment. The installation of the pressure sensors was relatively straightforward, and they were connected to the pressure lines of the target actuators.

When mounting the measurement microphones to the crushing plant, the effect of vibration was considered. According to the manufacturer, vibrations especially in the direction of the microphone diaphragm normal axis should be avoided, and the microphone should not be mounted directly on a vibrating surface (GRAS, 2023b). The frame of the mobile crushing plant and its other components are known to be vibrating surfaces, and therefore shock mounts for the microphones were used. The microphone mounts were custom-made in the factory and consisted of a fibre-reinforced rubber hose and general hose clamps or zip ties. The mounting of the microphone was evaluated to be very effective in dampening movement induced to the mount by hand, softly and gently returning to its equilibrium position. Thus, the mount was considered to provide significant vibration damping compared to directly mounting the microphone to the frame. Despite the manufacturer recommendation of avoiding vibrations, the microphones are stated to have a low sensitivity to vibrations, and therefore the mounting was considered to be sufficient for the application. To suppress the effect of wind and to provide additional protection from the environment, windscreens were used with the microphones. Mounting of the microphones is shown in Figure 18 and Figure 19.

***Figure 18.*** *Mounting of the vibrating feeder microphone without windscreen.*

***Figure 19.*** *Mounting of the light mast microphone with windscreen attached.*

Finally, with all sensors, cables, and DAQ equipment installed on the machine, the two cameras were mounted on the crushing plant. GoPro adhesive flat surface mounts were used, along with various GoPro mounting hardware to point the cameras towards their targets. 24 V DC power from the DAQ hardware cabinet rail was supplied to the proximity of the cameras using a power cable, and the voltage was stepped down to the USB (Universal Serial Bus) standard 5 V using suitable converters. The 5 V USB power could be used for powering the cameras from the crushing plant. Water- and dustproof hardware was used with the cameras to allow external power without losing the water and dust resistance. The voltage converters were protected from the harsh environment for the duration of the measurements.

### 5.4.2 Measurements during the crushing process

After the entire measurement setup was installed, the actual measurement period was started. The duration of the measurement period was three days, during which the measurement hardware was running, and the process was observed manually.

The goal of the manual process observation was to produce data with timestamps, augmenting the actual measurement data to allow different analyses to be performed after the field measurement period, and to track the uncontrollable field conditions as accurately as possible. An Android application called "*TimeStamp*" was used to conveniently add notes with accurate time reference in the field conditions. In addition to accurate time references with notes, the information collected to the application could be exported in various machine-readable formats including Comma-Separated Values (.CSV) -file, and JavaScript Object Notation (.json) -file. To prepare for the measurement period, certain pre-set notes were defined in the application, including process start and stop events, and events for normal process operation. These were used to mark events which were expected to be repeated several times during the measurement period. Normal operation notes were added as the machine was running normally without any disturbances. This was done to strengthen the understanding of the measurement data in the processing phase. The Android application user interface with example notes and timestamps is shown in Figure 20.


***Figure 20.*** *Screenshot of the TimeStamp -Android application used for timestamped notes during the field measurements.*

During the first measurement day, last sensor installations were made, and the data acquisition system was started. The system performance was observed by inspecting the data after a while of operation, and some problems were solved that emerged with the measurement setup. After the first measurement day, all the measurement hardware was working as expected, and the day was followed by two full measurement days. Some minor challenges were faced during the measurements, including a corrupted or damaged microSD -card on one of the cameras.

Process anomalies were expected to happen during the measurement period, and that was the case. By analysing the 152 notes made during the measurement period, a total of 11 individual anomalous events were identified. The anomalies are shown in Table 13.

***Table 13.*** *Process anomalies during the measurement period in the order of appearance.*

| | **Anomaly description** | **Effects** |
|---|---|---|
| 1 | Rebar buildup on the magnetic separator discharge chute | No major effects on the process (Mild) |
| 2 | Screen oversize conveyor jammed | Operator intervention was required to clear the blockage, no major loss in production time (Moderate) |
| 3 | Magnetic separator electric magnet function failed, resulting in rebar pieces ending up on the screen deck and blocking the screen | Blocked screen filled up with material, requiring process shutdown and few hours of manual work to clear the blockage (Moderate / severe) |
| 4 | Rebar pieces between the magnetic separator belt and frame - audible on the site and in the recording | No major effects on the process - rebar was removed during the next break (Mild) |
| 5 | Magnetic separator belt jammed. A wear part broke away from under the crusher and ended up being wedged between the main conveyor and the magnetic separator | Process automatically shut down. Removing the wedged part was quick, but replacing the damaged wear part resulted in a few hours of process downtime (Moderate / severe) |
| 6 | Minor damage in the main conveyor belt | No major effects on the process (Mild) |
| 7 | Screen oversize conveyor jammed | Operator intervention was required to clear the blockage, after which the same object momentarily blocked the return conveyor. No major loss in production time (Moderate) |
| 8 | Rebar pieces found from between the main conveyor frame and belt. | No major effects on the process (Mild) |

| | Anomaly description | Effects |
|---|---|---|
| 9 | Screen oversize conveyor jammed | Operator intervention was required to clear the blockage, no major loss in production time (Moderate) |
| 10 | Screen deck cleaned of rebar pieces | Screen deck had cumulatively collected various uncrushable objects, which were removed. Removal happens roughly once per day in this application (Mild, cumulative) |
| 11 | Rebar piece wedged between the main conveyor and the magnetic separator belt, jamming the magnetic separator | Process automatically shut down; operator intervention was required to remove the wedged piece. No major loss in production time (Moderate) |

As with the possible anomalies identified in chapter 4.4, the variety in the observed anomalies is wide as well. Some of the events, such as the screen getting blocked because of a magnetic separator malfunction, required the process to be stopped completely, and several hours of work to be conducted to resolve the problem and return the machine to operating condition. On the other hand, events like rebar build-up on the main conveyor structure or the magnetic separator did not cause any noticeable disturbances in the process and were resolved during the next natural break in the operation of the plant. The anomalies are classified on the same scale as presented in chapter 4.6. As stated in the chapter 4.2, it is normal for a CDW crushing process to have anomalies happening on an hourly basis. This was the case during the measurement period as well.

In general, most of the observed anomalies did not have serious consequences. Two events were classified between moderate and severe as they caused several hours of process downtime. However, both events were related to prototype testing of different components in the machine, which might have increased the risk for anomalies of these types.

As expected, some of the anomalies happened during a very quick timeframe, while others either developed slowly or were mild enough that the process was not required to be stopped. When researching the subject, different approaches must be utilized for different anomaly types, as for example applying quantitative methods to nearly instantaneous events like sudden conveyor blockages can be challenging. On the other hand, longer presence of an anomaly allows for quantitative comparison between the anomalous and healthy process states.

A common theme among the anomaly events shown in Table 13 is the interference between processed material or the process component itself, and a powered part of a process component. Jammed or damaged conveyors, blocked screen or parts wedged between powered parts of components all somehow obstruct the normal operation of the component, resulting in problems of various severity. Therefore, a single common measurable quantity in all the anomalies shown in the table except the number 1 is the power draw of the component associated with the problem. During this measurement campaign, power draws of every component were not measured as the research interests covered many other quantities as well. However, the conclusion from the three days of process observation is that nearly all observed anomalies could influence the power draw of their related components, and accurately measuring and analysing the power draw of every process component in different failure cases could be a good way to further research the topic.

# 6. FAULT DETECTION FROM RECYCLING CRUSHING PROCESS

After the measurement period, processing phase of the data was carried out. As the collected data set included several anomaly types with their own special characteristics, the entire measurement period could not be utilized in the scope of this work. In this chapter, the processing phase of the measurement data is described, and results from three anomaly cases are presented. As analysing all anomalies during the measurement period would be very time-consuming, two promising cases were selected, and they were accompanied by third case, which was the most commonly occurring failure mode during the measurement period.

## 6.1 Measurement data processing

When performing analysis on any given data, majority of the time spent goes to preparing the data and arranging it to a format from which different analyses are possible (Rattenbury, 2017). The work done in the scope of this thesis was not an exception, and a significant amount of time was required to prepare the measurement data in a way that different anomaly cases could be analysed.

As the measurement period was conducted in a real-world application and not in a controlled environment, the data relevant in the scope of this work was buried in the middle of irrelevant data from the normal crushing plant operation. The observations described in chapter 5.4.2 were designed to combat this, and developing an efficient workflow to combine the notes and measurement data was evaluated as being important. The main idea was to be able to inspect the notes quickly and efficiently along the measurement data, so that the anomalous events could quickly be located.

As the notes were made on a smartphone which could not easily be connected to the DAQ system, the time synchronization was an important factor in the successful workflow. The DAQ system time was synchronized with online-updated time before the measurement period, and the smartphone time was automatically updated from the internet by the operating system. Time synchronization accuracy requirement was evaluated to being rather loose, as the notes were made manually. The DAQ system time was estimated to match the near-exact time within few seconds, and this was evaluated to be sufficient for the application. The virtual data loggers in the DAQ system were synchronized with each other within the system, ensuring that all the measured quantities were time-synced.

For processing the measurement data, Python 3.10.0 and several libraries were used. Libraries included *Pandas* and *NumPy* for general data processing and numerical computing, *Plotly* for data visualization and *tsflex* for feature extraction. As all the processing was done on a local machine, special consideration was put to performance of operations to allow for rapid testing and prototyping of different approaches in the analysis phase. *Jupyter Notebook* was used for performing the actual analysis, enabling the use of Python and different libraries in a notebook-type user interface with code- and markdown cells that could be executed separately.

As a part of the work, a toolkit was developed in Python to perform various tasks related to preparing and analysing the data. The most important features included transforming the data from the output format of the DAQ system to fast and efficient feather files and reading the measurement data within an arbitrary timespan that could easily be selected. Additionally, features were developed to enable fast and efficient visualization of any given range of data. A feature was also developed to incorporate the notes taken during the field measurements into the raw visualized measurement data. An example of visualized data from the mechanical quantities measurement along with the notes is shown in Figure 21. Notes have been plotted as circular markers in the bottom part of the figure. When performing the analysis, the notes were accessible from the interactive and zoomable figure window by hovering them with a mouse. This way, the event time and description for the hovered event were shown. Notes were color-coded in the data processing phase to easily differentiate between different note types (anomaly / interesting event, normal state, other). In the figure, three distinct operation periods are visible, divided by two breaks in operation of the plant. The operation periods include sections of plant idle, with the equipment running without feed material. During the breaks, the measurement hardware was running, but the process or entire plant was shut down.


***Figure 21.*** *Example of mechanical data visualization – one day of measurement data is shown.*

By manually inspecting the interactive and zoomable high-performance plot of the measured mechanical quantities with the time-stamped notes, a good overview of the process state conveyed by the measured quantities could be established at any given moment during the measurement period. To support the awareness of the process state, videos from the machine input and output material flows could be referenced, as they contained the time-sync information as well.

Due to the nature of vibration- and audio data, visualizing and analysing the time-domain signals brings little value in evaluating their usefulness in process monitoring and anomaly detection. Therefore, a time-series feature extraction approach was used to condense the information from the oscillating zero-mean signals. Feature extraction was done using a Python library called tsflex (Van Der Donckt et al., 2022), which allows for very flexible calculation of features and is tailored for time series data. The scope of the work was to build knowledge on the fault detection subject from ground up, and therefore relatively basic features were used. The implementation of analysis was done in a way that allows easy and efficient further development regarding the feature extraction, and therefore builds a solid foundation for further research using more advanced methods. The statistical and spectral features used in the analyses are shown in Table 14, and the features were calculated using several Python libraries utilizing formulas shown in chapter 2.3.2.

***Table 14.*** *Features used in analysis*

| | **Feature** |
|---|---|
| 1 | Minimum |
| 2 | Maximum |
| 3 | Mean |
| 4 | Standard deviation |
| 5 | Variance |
| 6 | Skewness |
| 7 | Kurtosis |
| 8 | Zero crossing rate |
| 9 | Root mean square |
| 10 | Spectral centroid |
| 11 | Spectral flatness |
| 12 | Spectral bandwidth |

Selected features include statistical features to describe the signals on a very general level, and spectral features to extract information from the frequency domain. One of the hypotheses set before the research work was that the frequency domain representation of audio (or vibration) signal will change in the presence of an anomaly. For example, if the anomaly would include two metallic objects in sliding contact, the high-pitched sound produced was expected to shift the spectral centroid from the value of normal process condition.

## 6.2 Anomaly case 1 analysis – rebar in magnetic separator

The first selected anomaly case included a component which was assumed to be among the most problematic ones – the magnetic separator. During the measurement period, an observation was made that some rebar pieces had made their way between the belt and frame of the magnetic separator. An unusual sound was observable with human senses from the vicinity of the plant, and an assumption was made that the source of the sound was the magnetic separator. As the unusual sound was observed, the plant was running normally, and the situation was evaluated as non-critical, and the machine operation continued until next break. During the break, the magnetic separator was inspected, and several rebar pieces were found wedged between the belt and the frame of the magnetic separator. The rebar pieces were removed during the break, and machine operation continued normally. The magnetic separator and location of the anomaly is shown in Figure 22.

***Figure 22.*** *Magnetic separator. Rebar pieces were jammed between the frame (blue) and the belt and found their way along the entire circumference of the belt. Jammed rebar is not visible in this picture, and the gap between the frame and belt is illustrated with arrows.*

To illustrate the effect of the anomaly, spectrogram was used to present the audio signal in time-frequency domain. In Figure 23, normal process operation is shown on the left, while signal where the fault is present is shown on the right. The fault can be observed from the intermittent and steady pattern of impact-like high frequency events that have appeared in the time-frequency representation of the signal when compared to the normal process state. The intermittent pattern can be traced down to the design of the magnetic separator belt. The belt includes cleats to aid the removal of metallic objects picked up by the magnetic separator. In this case, some of the rebar pieces interfered with the cleats, and the intermittent sound was produced as a result.

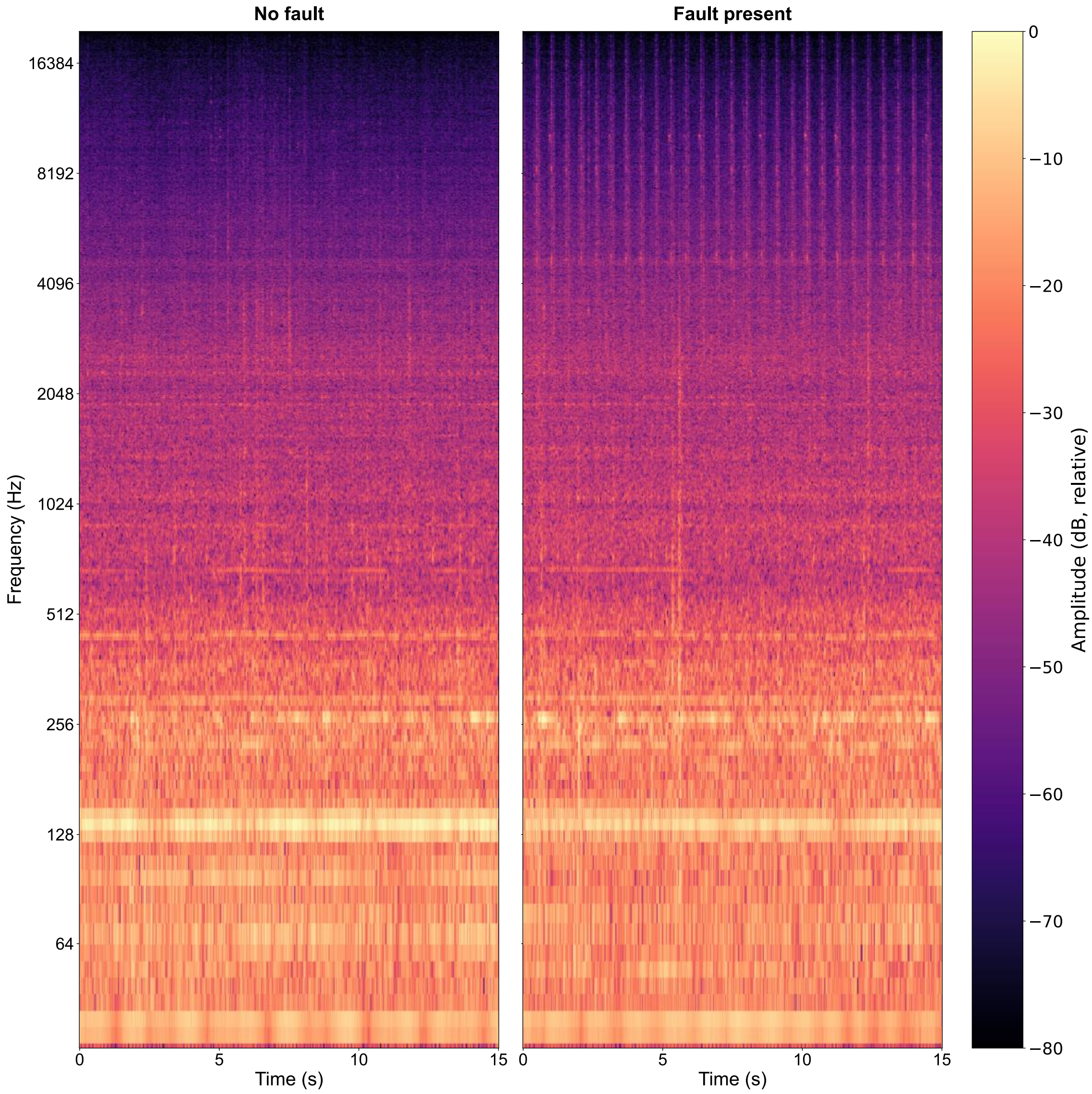


***Figure 23.*** *Spectrograms from normal machine operation and during the fault. Microphone 1 is used.*

While the spectrogram can be used for visualizing the change in frequency signature of the signal, it does not provide any quantitative measures which could be used in evaluating the possible effectiveness of fault detection using audio data. For this purpose, feature extraction method described previously was applied to the anomaly case. General process data visualization, similar to one shown in Figure 21, was utilized to find sections of machine operation where the process was run continuously. The notes from manual process observation were utilized, and one section with duration of 20 minutes was used to represent the faulty operation. For comparison, 5 different sections were selected to represent the normal operation, having a total duration of 1 hour and 11 minutes. The features were calculated with a window length of 5 seconds and stride of 5 seconds, essentially dividing the signal sections into 5-second non-overlapping parts. The window length of 5 seconds was selected based on the principle that the possible fault detection system should be relatively fast to prevent more serious failures from happening. On the other hand, the phenomenon in this case was evaluated to be detectable from few seconds of signal due to its relatively fast, intermittent nature. Longer window length could have provided more accuracy at the cost of response time.

As the number of features was relatively low, analysing the calculated features was possible without further processing. While performing the case study, the response of different features was analysed by plotting the features against each other in the form of scatter graphs. In Figure 24, an example visualization of three features is shown. In this example, spectral centroid, zero crossing rate and spectral bandwidth were selected as the analysed features, placed on the x-, y-, and color axes respectively. As can be seen from the figure, the faulty and normal 5-second samples form two clear clusters, which means that the fault presence has a relatively strong influence on features on both x- and y-axes. The spectral bandwidth indicated on the color axis is also contributing to differentiating the two states from each other, and from the relatively smooth gradient along the x-axis, it can be visually approximated that the spectral bandwidth and spectral centroid features have a somewhat strong positive correlation in this case.

The features shown in the figure behave expectedly. From the spectrograms in Figure 23 it can be concluded that the presence of an anomaly increases the energy in the higher frequencies when compared to the normal crushing process, and the response of the visualized features follows this. As most of the energy in the crushing process audio signal is found in the lower frequencies (visually 0 – 500 Hz), adding energy in the higher frequency range (visually 3 – 20 kHz) is expected to shift the spectral centroid towards the higher frequencies. The zero crossing rate (ZCR) describes the amount of zero-level crossings in the raw time-domain signal in a given time range, and has been widely used for several applications including spectral estimation (Kathirvel et al., 2011). The increase in higher frequency content is expected to increase the ZCR, which is exactly what happens. With the spectral bandwidth or spectral spread describing the spread of the frequency content around the centroid, it is also expected to increase when frequency content is added far from the area of most energy in the frequency domain.

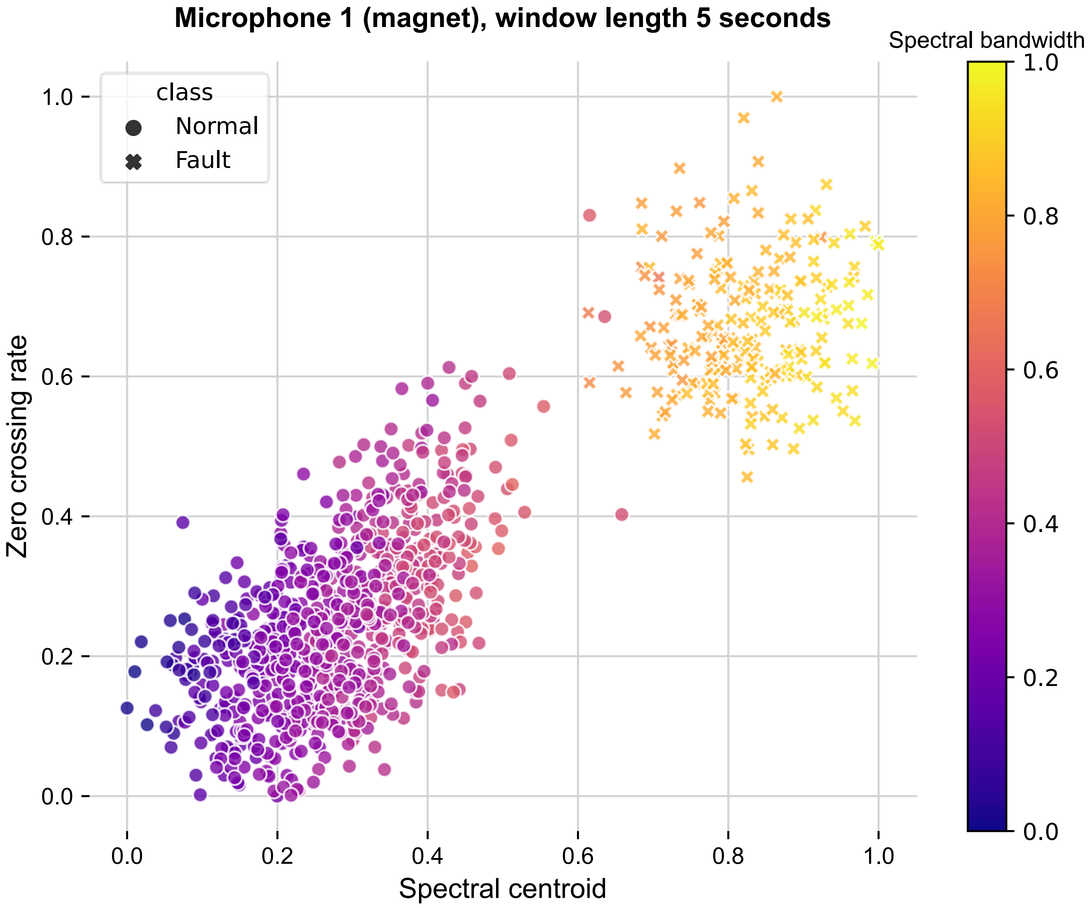


***Figure 24.*** *Spectral centroid, zero crossing rate and spectral bandwidth visualized for the anomaly in the magnetic separator.*

To further analyse the effect of the audio phenomenon produced by the anomaly, the information captured by the features was visualized with the t-distributed stochastic neighbour embedding (t-SNE) -algorithm. The result of the visualization is shown in Figure 25. By viewing the features independently, it was already concluded that the faulty and normal states are differentiable, but the t-SNE -algorithm further sharpens this conclusion by forming two separate clusters with no overlap. A single 5-second sample has ended up in the same cluster as the faulty ones, but generally the result clearly indicates the difference between the process states.

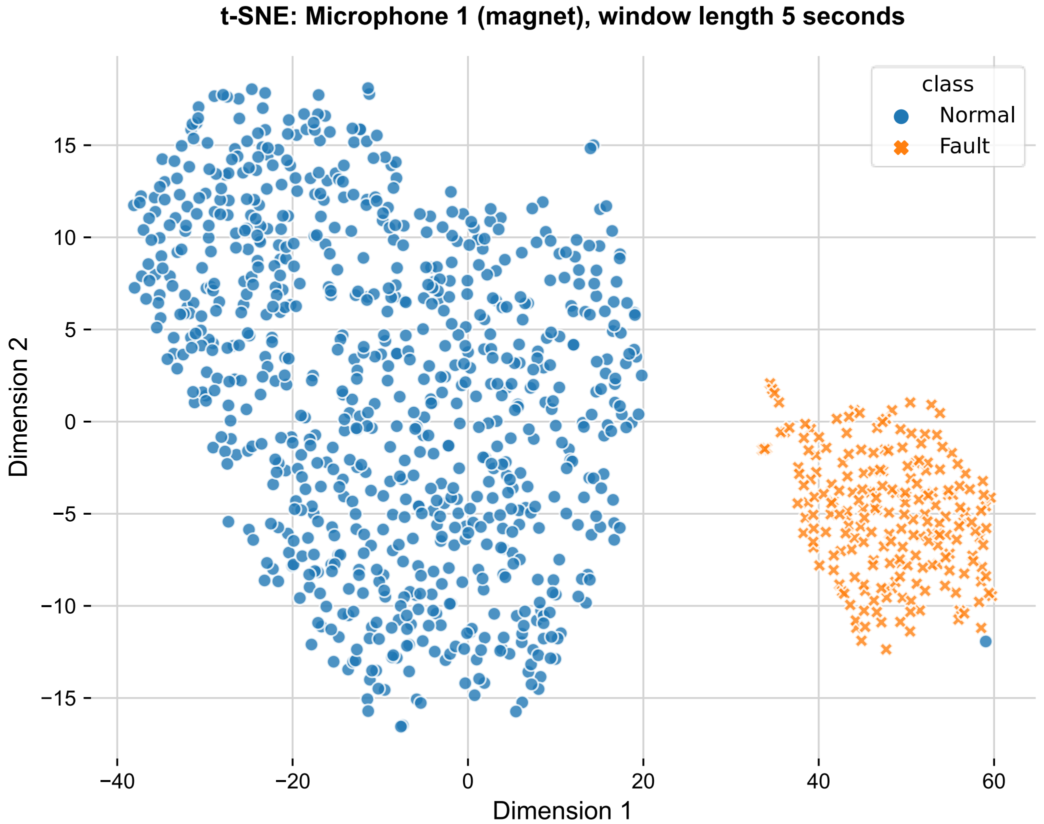


***Figure 25.*** *t-SNE -visualization for all calculated features from the magnetic separator anomaly audio signal.*

As the magnetic separator was considered as one of the most likely components for anomaly occurrence, an accelerometer was located on the frame of the magnetic separator during the measurement period. This anomaly case was partly selected, because the effectiveness of using the vibration signal can be compared to the audio signal. A similar feature extraction workflow was carried out for the vibration data from the accelerometer, and the results are visualized with the t-SNE algorithm and shown in Figure 26. As the figure shows, vibration data clearly differentiates the normal and anomalous process states, with the nonlinear dimensionality reduction algorithm producing two very clearly separated clusters.

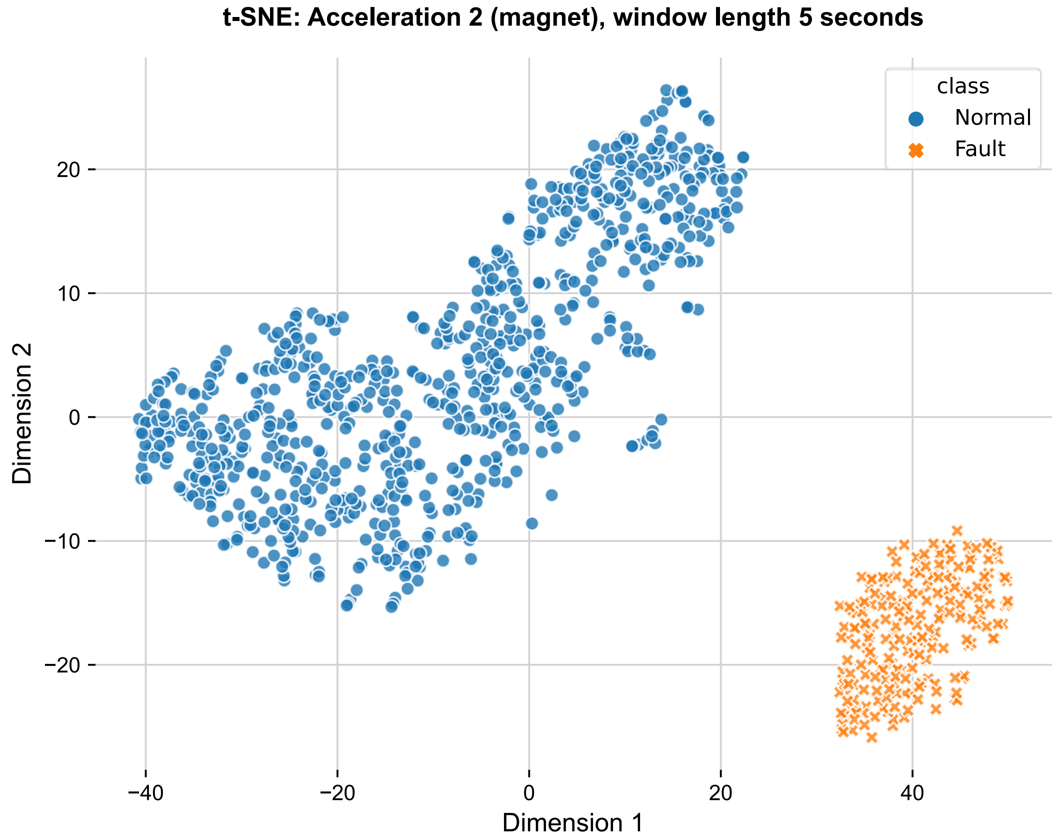


***Figure 26.*** *t-SNE visualization for all calculated features from the magnetic separator anomaly vibration signal.*

Overall, the rebar pieces jammed between the magnetic separator frame and belt produce phenomena that are detectable relatively easily. Both vibration and audio signals could be used in detecting an anomaly of this type, and the t-SNE results indicate that it should be possible to implement the detection with very good accuracy, as the faulty and normal states can be differentiated using relatively simple features. However, it is crucial to understand that the variety of anomaly types is huge and even if the failure mode is limited to the same mechanism as seen here (rebar between the magnetic separator frame and belt), the audio- and vibration phenomena might greatly differ from one case to another. In the form of a practical example, this failure case could happen in a way that the rebar pieces would not be interfering with the cleats in the belt, and therefore the possible sound produced would most probably be different, if there were any sound phenomena at all. The same thinking can be applied to the vibration data as well, as in this case the major change in vibration signature was due to the impact-type interference, which is very likely to produce vibrations which significantly differ from the normal process state.

## 6.3 Anomaly case 2 analysis – damaged main conveyor belt

The second anomaly case was selected as it was easily noticeable when first exploring the data, and persistent in nature, enabling the use of quantitative methods.

The disturbance occurred on one of the process components that were mentioned several times when collecting information on the typical process anomalies, the main conveyor. At a point during the measurement period, a small failure was noticed on the belt of the main conveyor. The belt failure is shown in Figure 27.

***Figure 27.*** *Main conveyor belt failure. The view is from the discharge area of the magnetic separator.*

When exploring the data, presence of the failure is clear. The failure had emerged between the measurement sections of two days, and the event leading to the failure was therefore not witnessed or captured. The failure appears in the data as distinct spikes in the electrical power draw of the conveyor. Time domain representations of normal conveyor idle and conveyor idle with the fault are shown in Figure 28.

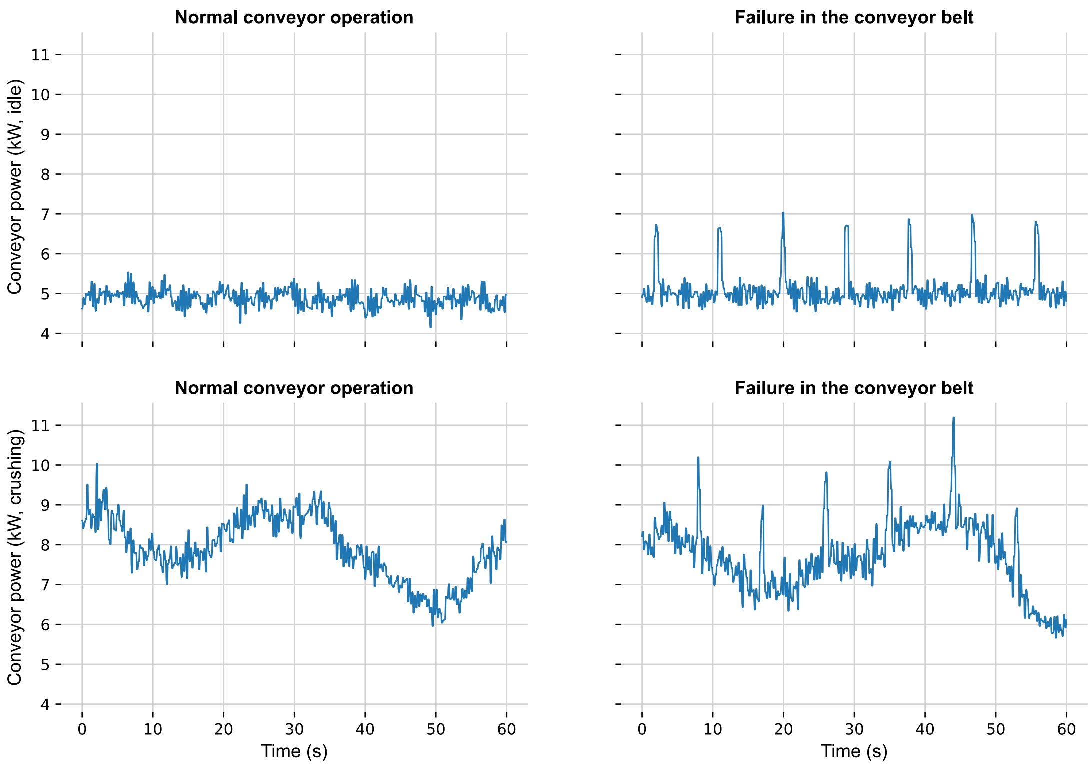


***Figure 28.*** *Main conveyor power draw during plant idle and during crushing – with and without the failure.*

While the time-domain representation effectively visualizes the anomaly, calculating a set of features from the signals can be used for evaluating the possibility of automated fault detection. As can be seen from the time-domain representation, detecting an anomaly of this type during the conveyor no-load condition could be implemented by monitoring the relationship between peaks in the power draw against the mean of the signal, but it must be noted that again the anomaly types can greatly differ and produce different signatures. The previously mentioned feature set was calculated and visualized with the t-SNE -algorithm, and the results are shown in Figure 29. As expected, the figure shows a clear difference between the faulty and normal states when the conveyor is running without material, but with this feature set, loading the conveyor immediately causes confusion in the detection. This is illustrated by the t-SNE algorithm not being able to form clear clusters which are separated. The result with loaded conveyor shows a certain degree of difference between the states as most of the signal samples are clustered in their own groups, but it appears that developing reliable detection for this fault type under conveyor load would require more suitable approaches.

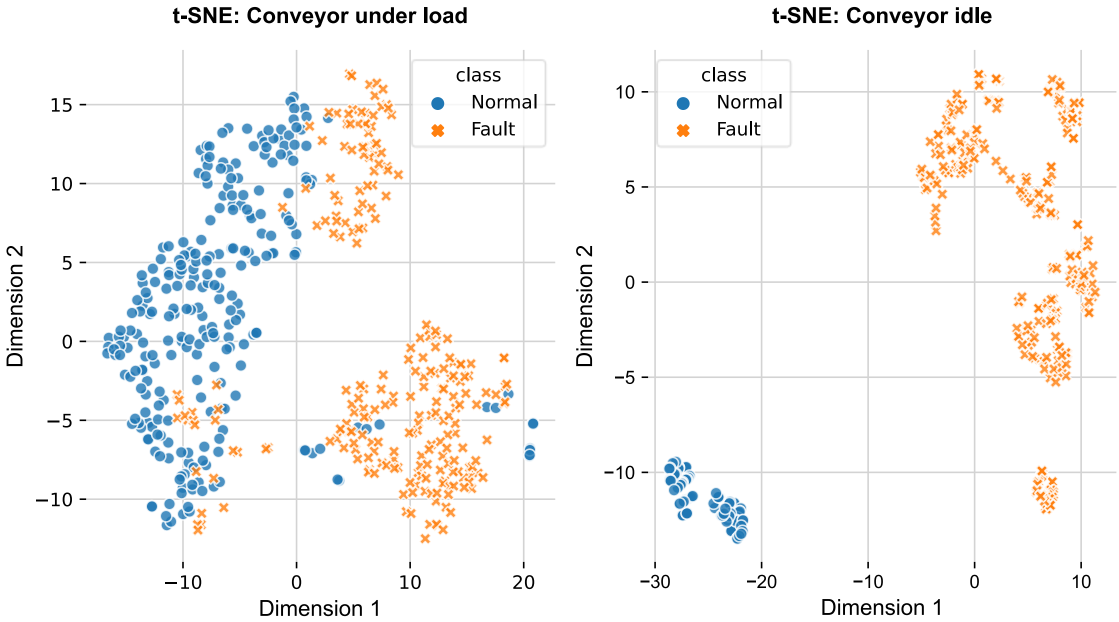


***Figure 29.*** *t-SNE visualizations for normal conveyor load and conveyor idle from the calculated features*

Generally, the damaged conveyor belt appears to be a detectable fault type. With the presented approach, faulty state could be differentiated clearly when looking at the conveyor power draw under no-load operating condition. As the phenomenon is produced by the ripped part of the conveyor belt getting caught somewhere in the structure of the conveyor, the detection performance for such fault will greatly depend on the way in which the belt fails. If the conveyor belt would have got damaged in a way that the damaged part was completely removed from the belt, the effect on the conveyor power draw could have been much less pronounced.

## 6.4 Anomaly case 3 analysis – blocked screen oversize conveyor

While the previous anomaly cases were chosen as they were noted to be promising in terms of successful detection from various measured quantities, the third anomaly case was selected to showcase a completely different anomaly event. As can be seen from the Table 13, the screen oversize conveyor getting blocked was the most common failure mode in the process and is therefore selected to be analysed.

The size of the impactor crusher product follows a probability distribution, and while majority of the crusher product falls in the "normal" size category, occasionally the output material flow might contain particles that are much larger than the typical maximum size. This can be caused by the breaker plates of the crusher withdrawing from their normal position due to excessive load, allowing the larger particles to pass through the crusher, or a piece of feed material might find a slot between the rotor blow bars, and be forwarded through the crusher without getting crushed. When a large particle makes its way through the crusher and rest of the plant, it ends up on the screen oversize conveyor, if a screening media is used. Due to the design of the oversize conveyor and surrounding structures, the particle may get wedged between the conveyor and the plant frame, causing a conveyor blockage. This process failure mode was witnessed three times during the measurement period. An example of such blockage is shown in Figure 30.

***Figure 30.*** *Relatively large natural stone jammed between the oversize conveyor and plant frame, preventing conveyor operation.*

The nature of this anomaly differs from the two previous ones. The anomalies discussed previously caused an effect on the process but did not force it to stop. This means that the anomalous state was present for a significant amount of time, and detecting the presence of the anomaly could be analysed by comparing the anomalous process state to a normal one. In this case, the problem appeared very quickly, and clearly cannot exist while the process is running, as the blocked conveyor would result in quickly spreading problems across the plant.

As a section of anomalous process state cannot be defined and the exact time of event is hard to determine, the analysis of this failure type is limited to qualitative methods. To investigate the possibility of detecting this anomaly type using the measurement setup shown, all data types were manually analysed. As the first method, the time-domain representations of the control system data and other mechanical quantities were inspected. An illustration of one of the three failure events is shown in Figure 31.

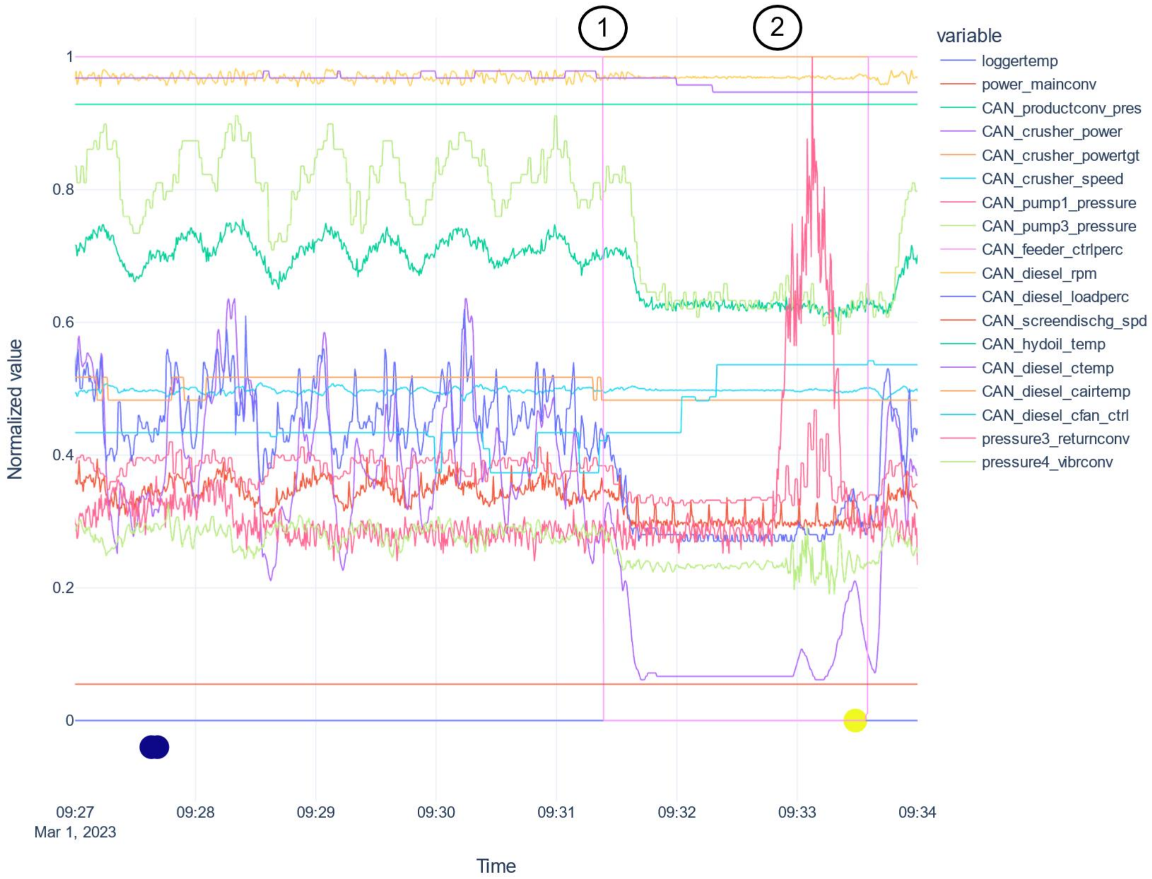


***Figure 31.*** *Mechanical signals during the conveyor blockage event. Operators noticed the situation and shut down the feeder (marked with 1), halting the material flow in the plant. After operator intervention, the blockage was cleared, and the return conveyor was temporarily blocked, resulting in high hydraulic pressure (marked with 2). Values are normalized to fit the same graph.*

By analysing the event based on the data shown in the figure, it can be stated that the formation of the failure event cannot be easily seen from the data. The variation in almost all measured parameters is significant during the 4 minutes of normal operation shown in the figure, and from the experience gained during this work, the behaviour is very similar to any other normal process operation. The first indication of the failure event is the feeder control percentage switching to 0, which is done by manual control input from the operators. All three instances of this failure mode were thoroughly analysed in the same way, and no other indications were found. The result is expected, as the oversize conveyor operation was not included in the measurements. The closest measured quantity was the hydraulic pressure of the return conveyor, which is fed by the oversize conveyor. In theory, the power draw and therefore hydraulic pressure of the return conveyor should decrease to an idle value when the oversize conveyor is blocked, but due to the design of the return conveyor, this is not the case. A confirmation for this was found on the data, as during one measurement day the hydraulic pressure of the return conveyor increased significantly every time it was left operating without material.

In addition to the control system and other mechanical data, the vibration- and audio measurements were also inspected. A spectrogram representation of the audio signal of the microphone closest to the oversize conveyor is shown in Figure 32. Several factors about the process are interpretable from the spectrogram, but no evidence of early indications of oversize conveyor blockage are found. The spectrogram reveals information such as the feeder shutdown (Several frequency components attenuated a bit after 4:10 mark), the diesel engine cooling fan control (frequency component going up and down a little above the dominating frequency component around 130 Hz), component RPM fluctuations (waviness of several frequency components), crusher operation (majority of short wide frequency-range events) and others. Different phenomena can be further highlighted by changing the parameters for the spectrogram.

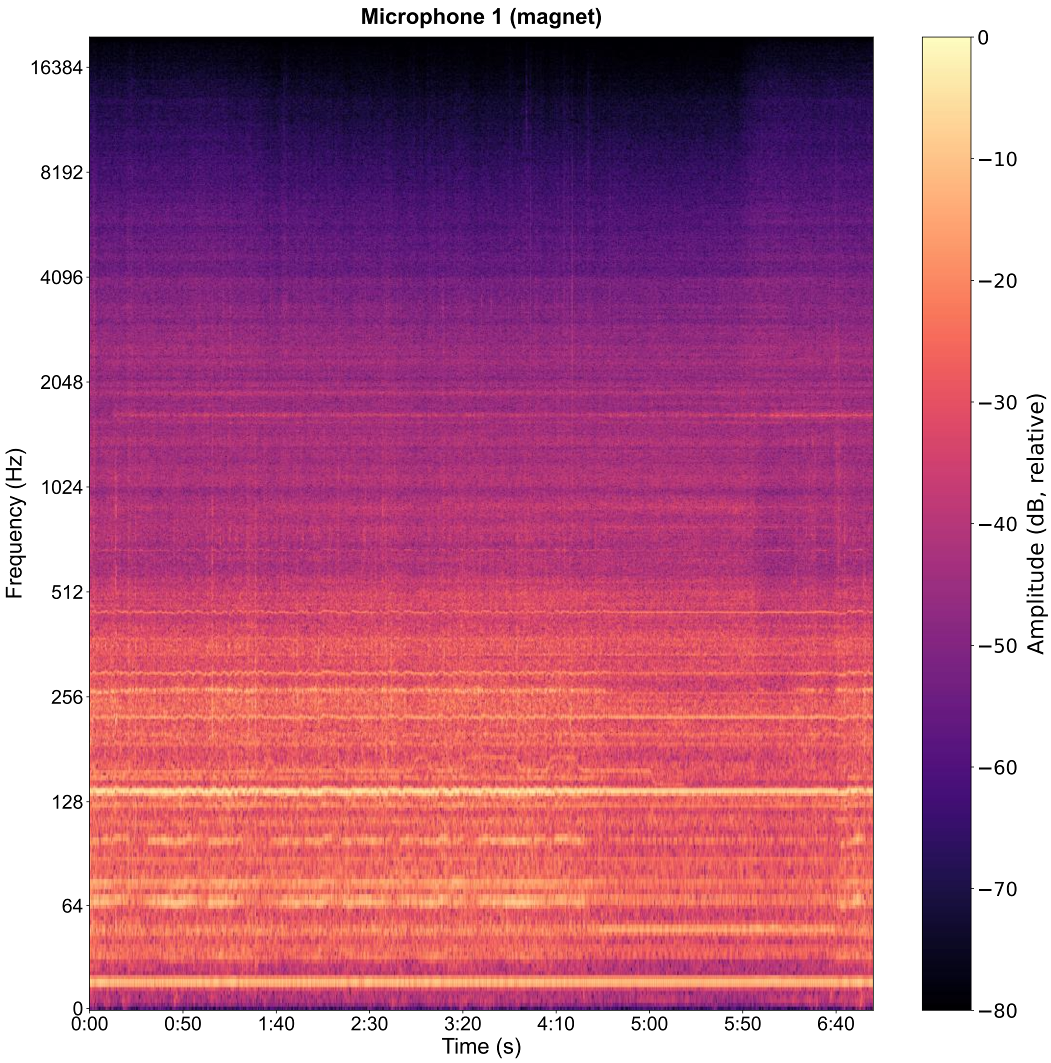


***Figure 32.*** *Spectrogram representation of the conveyor blockage event. The timespan corresponds to the previous graph, and the feeder is shut down a bit after the 4:10 mark.*

The vibration signal of the plant frame was also manually analysed in time- and frequency domains, but the results are very similar to the audio data – blockage of the oversize conveyor is so quiet and unintrusive event that the possible associated audio- and vibration phenomena are too weak to be easily noticed. This conclusion is supported by observations with human senses, as the event was hard to notice on the site with no visual confirmation. The audio data was also reviewed by listening to it, and while the audio recordings carry a very good quality auditory representation of the process, the oversize conveyor blockage cannot be heard from the recordings.

# 7. CONCLUSIONS

In this work, a feasibility study was conducted to research the possibility of monitoring the demolition waste recycling crushing process with mobile impactor crushing plants. The research problem and therefore research questions were formed to allow a wide variety of possibilities for the execution of the research. During the progress, different constraints narrowed down the scope, which eventually converged to the final form.

As stated in the first research question, a clear objective was to gather information about the construction and demolition waste crushing process, and especially on the process anomalies. In the literature review, it was found out that thorough understanding of the system in question is very important when developing model- or knowledge-based fault detection for any system, and the research question was therefore set very well. The interview study provided an overview on the information inside the company, and solid summary was built based on the results. The most significant findings included 11 failure modes, describing different ways in which the crushing process can fail. After the interviews, the failure modes were further analysed, and knowledge on their causes and effects was built. Additionally, the interviews yielded information on the normal operation of the crushing process, which again is important system knowledge. One of the common messages from the interviewees was that processes are different from one another, and it must be noted that the 11 identified failure modes do not necessarily convey a comprehensive understanding of how the process can fail. Based on the experience gained during the work, the characteristics of a certain recycling crushing process can accurately be determined only by getting familiar with the process and forming an all-embracing representation might lead to inaccuracies.

Implementing the measurement period was not explicitly defined in the research questions but it was still an important part of the work. In the planning phase, many questions regarding the measurement campaign were still open, and the success of the campaign could not be guaranteed, as it could not be carried out in a controlled environment. However, the measurement period ended up being very successful, and the objectives set for the measurements were met, in terms of this thesis and other targets. The success of the measurement campaign was a result of a suitable machine, application, and the appearance of a variety of anomalies during the measurement period, as well as good performance of the DAQ equipment and other hardware, such as the selected microphones.

The remaining research questions were answered theoretically in the literature review, as well as empirically with the analysis of data collected during the measurement campaign. The only concept connecting the results and answers is variability. In the literature review, it became clear that the field is widely studied, and almost a limitless selection of approaches and methods have been developed and tested, and there is no universal way of monitoring different processes. Knowledge-based systems and mathematical models were addressed as often being hard to build, especially when considering complex processes, and often the proposed solution was to build data-driven models using modern deep learning techniques, and possibly combine them with accurate expert knowledge of the process in question. The research questions from number 2 to 4 were set to find out how analysing data of different types can be utilized in detecting the anomalies discovered in the first research question. A variety analytical, knowledge-based, and data-driven approaches were discovered and shown in the literature review, addressing different types of data. An exhaustive theoretical answer would require a lot more work.

The data from the measurement campaign was used to analyse three different anomaly cases to test few approaches in practice. Approaches included signal processing techniques, traditional time-domain visualizations, as well as concepts from the machine learning discipline. Feature extraction was performed to demonstrate how audio- and vibration data can be transformed to computer-interpretable form using relatively simple and efficient statistical and spectral features. The feasibility of anomaly detection was evaluated by analysing the behaviour of time-series signals, the time-frequency representations, or by visualizing the information captured by the computed features in two dimensions using the t-SNE dimensionality reduction algorithm. According to the analysis, detection for certain failure modes can be developed using audio- or vibration data, but the nature of the anomaly plays a huge role in what is possible. Example of a possible case is shown in anomaly case 1. Other data types, such as process component actuator electrical power draw, can also be useful for anomaly detection, as demonstrated by the anomaly case 2. Anomaly case number 3 demonstrates, how different failure modes require very different approaches, and in this example, detection of the event could not be implemented.

The results of the failure case -based data analysis provide empirical answers to the research questions 2 – 4. The second research question considers the use of plant control system data in detecting process anomalies. The results from anomaly case 2 showcase the potential of utilizing actuator power draw measurement. While the main conveyor power draw was in this case measured directly and not via the control system, similar results could be achieved if the power draw measurement was added to the CAN bus. To address the third research question on audio signal analysis, anomaly detection was demonstrated in the results of anomaly case 1. The first anomaly case was also used to demonstrate the usefulness of vibration signal, which was considered in the research question 4. An important factor in the analysis for all cases was the clear big picture, which was formed using all available data types as well as metadata and made the analysis of failure cases possible based on individual signals.

Overall, monitoring a demolition waste crushing process can be stated to be a complex task. The variability of the normal state of the process as well as the possible anomalies creates an environment, where the system should be able to adapt to different "operating points" of the process and determine the normal system state on the fly. The system should also be able to distinguish a range of possible anomalies and to separate them from the normal process events, some of which are very random in nature. Approach for development of such system could first focus on only a few known failure modes, which would reduce the complexity. This would require additional research to investigate the area of focus and associated phenomena, after which the approach could be further defined in terms of what is measured and how the data is analysed. Another proposed approach could be the electrical power draw measurement of every process component, and development of a fault detection system based on them. This is suggested as nearly all anomalies faced during the measurement campaign had an association with the power draw of some process component. Based on previous experience, this approach would include its own challenges as well, but research on the subject could at least provide more insights on the challenging topic.

The business of aggregate production and therefore the development of associated machinery is based on effective processes. The demolition waste crushing process is relatively prone to different disturbances, and every way of preventing these problems results in substantial improvement to the operation of the processing plants. Direct benefits are easy to see in financial and ecological aspects, as less process downtime results in less wasted resources. However, an important and possibly even understated aspect is the increased user-friendliness of the machines. In the current state, operator intervention is regularly required as process anomalies lead to different levels of malfunctions. Manual intervention is known to often be an annoying task, which might pose even more significant cascade effects than initially expected. If operators get frustrated with the problematic process, possible consequences might range from loss of trust towards the machines to neglecting safety precautions, which is obviously far from desirable. Therefore, developing means for reducing process interruptions can be reasoned from multiple perspectives. While the findings made in this work support the theory that such system can be built at least to some extent, further research and development of a process monitoring system is justified.

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# APPENDIX A: NORMAL OPERATION AND ANOMALIES OF RECYCLING CRUSHING PROCESS WITH MOBILE IMPACTORS – INTERVIEW SUMMARY

**Feed material**

- Pre-processing/pulverizing the feed material is key to successful recycling crushing processes. The feed material must be something that the crusher has an ability to process: the machine should not be fed with oversize feed material, included rebar pieces and other metal parts must be cut to short enough length, etc.
- The feed material may contain a lot of metallic parts. This is described: “The magnetic separator by-product stream value can almost match the fuel costs of operating the machine.”
- The feed material is very heterogenous, and the crusher is fed “a bit of everything.”
    a. For example: oversize particles, steel rebar and other metals that are too large, etc.
    b. Even if the feed material was only concrete and nothing else, different types of concrete exist with different properties.
- Crushing the steel rebar -reinforced concrete is the most challenging of all recycling crushing processes.
- As an example: in one country, where a lot of recycling crushing is done, feed material can be “very good” [*in terms of problem-free process*]. On the other hand, the next feed stockpile can include “anything”.
- Some of the most common objects in the feed material are [*in addition to concrete/bricks/other*]:
    a. Steel rebar and other metallic materials
    b. Pieces of electric wire
    c. Pieces of steel wire rope
    d. Lighter material such as tarpaulin etc.
    e. Insulation material, floor matting, etc.
    f. Structural foundation piles, natural stones
- Steel rebar in the feed material are typically embedded inside pieces of concrete either fully or partly.
    a. A small chunk of concrete with a hook-shaped piece of rebar embedded in it catches itself to the machine structures easily.
        i. These are both found in the feed material and formed by the crusher.
    b. Return conveyor structure is often a place where these get caught.
- An example: In one application, old, large grain silos were demolished and crushed. The material included plenty of steel rebar among the concrete. On another site nearby, brick- and glass material from building demolition was crushed, and the material did not include any tougher parts.

- With very light feed materials such as the mentioned brick- and glass material, a problem can be that the machine cannot be fed with enough material to achieve the full capacity/potential of the plant. In this case, the capacity is higher when compared to strong materials, while the machine could perform even better.
    a. When crushing asphalt, the limiting factor is the capacity of the screen.
    b. Insulation materials are often well separated from the feed material.
    c. If wire rope is included in the feed material, it is usually not very problematic.

**Normal state of the recycling crushing process**

- The process can either stay in a relatively steady state or change from a state to another very heavily. Fully depends on the operator of the machine, environmental and other conditions and on the overall type of work being conducted.
    a. For example: with "clean" feed material, the recycling crushing process can be problem-free and stable. On the other hand, the feed material might include almost anything, depending on several factors.
    b. One thing affecting the process state is the setting of the crusher.
        i. Adjusted both when switching from one product size distribution to another, and when compensating for the worn blow bars.
    c. Different configurations of the feeder and pre-screen have an effect on the process.
        i. An example is a known customer that sometimes operates their machine with the pre-screen completely blocked with a blanking plate.
    d. Process state is changed by the side conveyor being either in use or bypassed.
    e. If the process is run in an open-loop -configuration, the state differs from normal, closed-loop operation.
    f. Crusher rotational velocity can be changed at least in some machines, this is another factor which can alter the state of the process.
- Even in normal state, the recycling crushing process has a lot of interruptions. The process can be interrupted more than once per two hours. [*This is significantly more than "normal" crushing processes, for example normal rock crushing*]
- Sometimes the process operators try to maximize the capacity of the crushing plant, and sometimes the machine is run more carefully.
- The process is very variable:
    a. One factor comes from the feed material.
    b. Another factor causing variability is the way the plant is fed. Operator actions have an effect on the material which ends up in the machine, the pace of feeding, idle periods, etc.
- One of the sources for process variations is the crushed product. The product has multiple effects on the configuration of the machine. The wanted product is driven by the market demand and therefore depends on the area where the machine is operated.

**Process anomalies in mobile impactor plants**

- Rebar pieces find their ways to every possible spot in the main conveyor and other conveyors as well. If the rebar pieces end up in the idle rollers or other critical places, the formation of a problem begins.
- [*One of*] The most common anomaly with mobile impactor plants:
    a. A pile-up of steel rebar or similar material is formed inside the plant, ending up on the main conveyor, under the plant power unit.
    b. The pile-up might remain inside the plant, rolling around in the material stream, collecting more and more steel rebar.
    c. If the situation further escalates, the pile-up might block the material flow inside the plant completely, resulting in a very serious blockage and roughly 8 hours of manual work to resolve the blockage.
    d. The pile-up might also get transferred forwards, ending up under the magnetic separator.
        i. If the magnetic separator is light, it might be able to rise, allowing the pile-up to be pushed out of the process by the magnetic separator belt.
        ii. If the magnetic separator is heavy, it cannot rise, and forces the pile-up to stay between the magnetic separator and the main conveyor. This blocks the material flow on the conveyor, and the blockage quickly accumulates material inside the plant.
        iii. The conveyor might also be overloaded, losing speed and eventually leading to similar blockage.
- Another description of the situation mentioned above: The pile-up is “born” under the crusher rotor, slowly collecting pieces of rebar. The pile-up is kept from moving forwards by the crusher rotor.
    a. The vibrating conveyor after the crusher cannot move the pile-up forwards very fast, and the rotor pushes it back on every rotation.
    b. New rebar pieces can join the pile-up, making it bigger.
    c. Finally, the pile-up gets moving in the process, and causes a blockage in places mentioned above. The blockage of the entire machine happens very fast, and the aftermath is a day’s work.
    d. The pile-up is often removed using oxy-acetylene cutting or angle grinders.
- Sometimes a lot of fine material is passed through the pre-screen.
    a. If this stream is directed towards the end of the process and the side conveyor is not in use, the screen might suddenly receive a lot of fine material.
    b. The fine material goes through the screening media, and might overload the product conveyor, even causing a blockage.
    c. Maybe one third of the feed material can bypass the crusher.
- The feeder can be blocked.
    a. The pre-screen can collect rebar pieces, requiring regular manual work to remove.
- Screening media can get blocked.
    a. This is not the most serious problem.

- Large enough steel pieces can get stuck to the magnetic separator by the magnetic force.
    a. Results in the magnetic separator belt to stop moving and requires manual work to resolve.
- Conveyors (especially hydraulic) can lose speed under heavy load.
    a. Solved by pausing the feeding intermittently.
- Bypass chute can get blocked.
    a. In certain conditions, material freezes to the edges of the chute, and eventually the chute gets completely blocked.
    b. This can be seen from the increased fine fraction on the feeder and on the pre-screen.
    c. Not very common, applications exist where this does not happen.
- A big problem is the crusher breaker plate getting jammed in the withdrawn position.
    a. When the breaker plate is withdrawn due to hard loading (as designed), it does not necessarily return to its original position.
    b. The breaker plate might stay in this position for a longer time, requiring manual work to fix.
    c. When the breaker plate is in its withdrawn position, oversize material ends up through the crusher, and might end up blocking the screen oversize conveyor.
    d. Oversize rocks might cause problems in other parts of the process as well: between the magnetic separator and main conveyor, roll backwards on the return conveyor or get stuck in the return conveyor structure.
    e. Even normal withdrawal of the breaker plate might cause the same effects. The change in the crusher product size distribution can be big, as the breaker plate can move up to 100 mm.
    f. Several mentions of oversize conveyor and return conveyor jamming due to this phenomenon.
    g. Example: A customer has installed a camera on the return conveyor, from which the oversized material can be observed.
- On the feeder, rebar and other metals going through the pre-screen media is always bad, and they cause problems either on the pre-screen or the bypass chute.
    a. Especially problematic if the excavator operator cannot see to the pre-screen, as the problem build-up cannot be monitored.
- Long rebar/metal pieces and wires can be wrapped around the crusher rotor.
    a. In mobile impactors, more space exists between the rotor and wear plates on the sides of the crusher.
    b. Not very common
- Screening media collects light materials, such as tarpaulin etc.
    a. These do not typically cause very serious problems.
    b. The magnetic separator mostly removes ferromagnetic objects.
- Conveyor structure around the magnetic separator collects rebar pieces.
    a. In the worst case, this results in a destroyed conveyor belt.

**Process phenomena, sounds, etc:**

- Different process states produce different sounds, this is clear.
    a. Frequency content of the process audio signature changes
    b. Example: amount of material on the feeder affects the sound produced by the feeder.
    c. Intermittent material flow produces different sounds in the process than steady flow.
    d. Example: The vibrating conveyor can act almost like a drumhead, reacting to variations of the material flow.
        i. Large metal objects can probably be heard from the material stream.
    e. Example: at least the type of the steel object, angle of impact and size influence the sound produced when the object travels through the crusher. The same is true for the vibrating conveyor.
        i. Plastic deformations of the metallic objects absorb energy and therefore less sound is produced.
        ii. When an object hits the top of the crusher chamber, sound is produced.
- When a conveyor is jammed, the hydraulic pressure or electric power most probably reacts.
- Breaker plates withdrawing can be heard with human senses.
    a. Especially true for the breaker plates returning to their normal position.
- The screening media becoming loose can be heard.
- Screening media becoming blocked can possibly be detected from the sound of the screen.
- In general, loose joints in the vibrating equipment are detectable by sound.
- Objects wrapped around the crusher rotor might also produce sound.
- Steel pile-up getting jammed under the power unit might result in vibrations, as the pile-up can rotate around while being pushed by the conveyor.
    a. This can also be heard with human senses.
    b. The sound can be described as “scratching”, and the mechanism for sound production is not well known. However, the sound might be a result of the rebar pile-up lifting other steel pieces up from the material flow and making them scratch the structures. These pieces do not get attached to the pile-up, and rather keep going forward in the process.
- Foreign objects on the screening media can significantly alter the sound produced by the screen.
- Steel wire around the crusher main bearings has sometimes been found out as the reason for weird sounds from the machine.
- Several sounds appear and fade away all the time during the process.

**Asphalt as feed material**

- In the case of asphalt recycling the bitumen dust is problematic
    a. Sticky dust blocks the engine radiator. A customer regularly removes the radiator, cleaning it separately.
- Asphalt is crushed with impactor plants using a wide setting in a way that the rocks in the asphalt do not break but the structure of the asphalt is broken.