Real Time Mining
2nd International Raw Materials Extraction Innovation Conference
26th & 27th March 2019 in Freiberg
Proceedings of

Real-Time Mining

2\textsuperscript{nd} International Raw Materials Extraction Innovation Conference

26th & 27th March 2019

Freiberg

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Dear Participant of the 2nd Real-Time Mining Conference,

it is our honor to welcome you to the second conference on Real-Time Mining, an International Raw Materials Extraction Innovation Conference, which is bringing together individuals and companies working on EU-sponsored projects to exchange knowledge and rise synergies in resource extraction innovation. The topics include:

- Resource Modelling and Value of Information;
- Automated Material Characterization;
- Positioning and Material Tracking;
- Process Optimization;
- Data Management.

The conference has been initiated by the consortium of the EU H2020 funded project Real-Time Mining as a platform for inter-project communication and for communication with project stakeholders. It brings together several European research projects in the field of industry 4.0 applied to mineral resource extraction. These are the projects VAMOS, SOLSA and UNEXMIN. It is hoped this platform serves for lifting synergies, strengthening the project focus and to initiate potential further developments and exploitation activities.

After the first successful conference at the Koninklijke Industrieele Groote Club, in Amsterdam, the Netherlands, the second conference is being hosted in Freiberg, Germany. This year, the conference has been organized in conjunction with the demonstration day of the Real-Time Mining project, which marks the successful completion of the project by demonstration innovative approaches and technology developed within the past four years at the Reiche Zeche mine.

We hope you enjoy your stay in Freiberg and the conference.

Kind Regards and Glückauf!

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TU Delft

Jörg Benndorf
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Freiberg, March 2019
# Table of contents

Developing an underwater robotic platform to explore flooded mines – the state of the UNEXMIN project  
Luís Lopes et al.  
11

SOLSA-Field tests: indispensable for reaching SOLSA Goals  
Monique Le Guen, Beate Orberger  
18

Remote Reading Instrumentation Requirements for Longwall Automation in Underground Coal Mines  
Charles Sweeney, Nathan Owen  
20

Geochemical mapping of drill core samples using a combined LIBS and XRF core scanning system  
Marinus Dalm, Marijn Sandtke  
22

Evaluation of sensor technologies for on-line raw material characterization in “Reiche Zeche” underground mine - outcomes of RTM implementation  
F. S. Desta, M. W. N. Buxton  
32

Evaluation of Thermal Imaging based on LWIR cameras for Rock Characterisation  
Britta Eichentopf et al.  
49

Moisture effect on hyperspectral analyses tested on bauxites and Ni-laterites samples  
Sylvain Delchini et al.  
62

SOLSA Drill, a modular and versatile tool for high quality sampling in heterogeneous soils  
Harm Nolte et al.  
64

DriftLess: Underground Positioning using Bias Compensation for Inertial Sensors combined with UWB  
J. Rojer et al.  
65

Multispectral imaging of minerals in flooded mines – a case study  
Richárd Zoltán Papp et al.  
84

UNEXMIN underwater 3D mapping with sonar and laser scan  
José Miguel Almeida et al.  
86

Unlocking Online Sensor Potential: Innovative Approaches for Real-Time Resource Model Updating  
Jörg Benndorf et al.  
88
Virtual Reality Mine Planning and Operation Control
David Buttgereit 112

Use of time series event classification to control ball mill performance in the comminution circuit – a conceptual framework
J.R. van Duijvenbode, M.W.N. Buxton 114

The Use of Production Scheduling Analogs for Reconciliation of Mining Reserves
J. Neves et al. 124

Data exchange by WLAN and TTE in underground mining to a Supervisory Control And Data Acquisition system basing on OPC Unified Architecture
David Horner et al. 126

Geotechnical parameter definition from machine performance measures for sonic drilling
E. Clausen et al. 128

An Approach to Optimize Underground Mining Processes by the Use of Real-Time Data
Johannes Hornung, Lars Barnewold 149

Improved grade classification through sequential resource model updating using real time monitoring data in underground mining
Wenzhuo Cao et al. 155

Unraveling the Capability of Artificial Intelligence for Prediction of Rock Fragmentation
Duah Philip et al. 157

Uncertainty Integration in Dynamic Mining Reserves
J. Neves et al. 178

You can’t improve what you can’t see – The Talpasolutions’ approach to utilize real time machine data, seeking enhanced mine productivity and efficiency
Mirko Liebetrau et al. 179

Testing of prototype robot UX-1a for exploration and mapping of flooded underground mines
Emil Pučko et al. 188
Developing an underwater robotic platform to explore flooded mines – the state of the UNEXMIN project

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ABSTRACT:

The UNEXMIN project is developing a multi-robotic platform for the autonomous exploration and mapping of underground flooded mines. The system uses non-contact methods for the 3D mapping of the mines’ structures. With the geological and spatial knowledge obtained with the UNEXMIN technology new scenarios for the exploration of flooded mines can be considered while assessing data that cannot be obtained otherwise without major costs and safety risks.

UNEXMIN currently has one fully operable prototype – UX-1a – already tested in the first two trials proposed, at the Kaatiala mine, Finland (June 2018) and at the Idrija mine, Slovenia (September 2018). This prototype is the culmination of many efforts including the validation and simulation of basic robotic functions such as movement, control and mapping capabilities, the design, testing and adaptation of custom scientific instruments, the testing of navigation, perception and 3D mapping tools and finally the development of post-processing and data analysis tools. The integration of UX-1a, both with basic instrumentation and the scientific array and effectively tested in a pool environment, was due in April 2018.

The Kaatiala and Idrija trials aimed at testing the prototype in real application environments and to further test and improve the instrument array and the robot’s capabilities. UX-1 was successfully operational, although with an umbilical used for data transfer and control for security reasons, in both trials. Geological and spatial raw data obtained from the trials is now being post-processed and analysed to create 3D models of the mapped environment. At the same time autonomy is being improved and implemented. The project is now producing the second UX-1 and aims at having it ready for the next trial at the Urgeiriça mine, Portugal, where two robots UX-1 will work together in a collaborative way.
The final goal will be reached when the platform of three robots map the entire flooded section of the Ecton Mine, UK, that no one has seen for more than 160 years.

1 Introduction

UNEXMIN (Underwater Explorer for Flooded Mines, Grant Agreement No. 690008, www.unexmin.eu) is a European project funded by the European Commission’s Horizon 2020 Framework Programme. Since February 2016 the project is developing a new autonomous multi-platform robotic system, formed by three robots – called UX-1 a, UX-1b and UX-1c – to explore and map flooded underground mines. The information obtained by UNEXMIN’s robotic platform will provide relevant new geological and spatial data that currently cannot be obtained in other way without major costs (e.g. dewatering costs) or risks (e.g. using human divers for exploration). With actualised data from these mines it will be possible to develop new or update already existing geological models at local and regional kevels, and, ultimately, open the consideration of new exploration scenarios for Europe’s valuable raw materials.

2 Concept and approach

The UNEXMIN consortium proposed this project as a response to the European Commission’s 2014-2015 Horizon 2020 Societal Challenge 5-11d (SC5-11d) named “New sustainable exploration technologies and geomodels” (European Commission, 2015a) and to the challenge of “Ensuring the sustainable supply of non-energy and non-agricultural raw materials” in the EU (European Commission, 2015b). Thus, while formulating an answer to these topics, UNEXMIN intends to help the EU to lessen its dependency on the import of raw materials by providing a unique solution for sustainable exploration scenarios in abandoned flooded mines while at the same time improving the knowledge base for mineral potential in Europe. UNEXMIN’s aim and visions are in line with European policy for raw materials, such as seen in the Raw Materials Initiative (European Commission, 2008) and others1.

It has been accounted that the number of closed mines in Europe total 30,000 (International Society of Rock Mechanics, 2008). Many of these are still considered to have unexploited quantities of mineral raw materials. This arises from the fact that mineral extraction often stops, not because of mineral depletion, but due to economic and technological constraints. However, as today’s prices on mineral commodities are increasing, and demand has drastically shifted – what was considered as contaminant 50-100 years ago, is regarded as commodity today (e.g. fluorite in Pb/Zn mines). Thus, former underground mines are a new target to consider for mineral exploration due to increased commodity prices and demand that can make extraction operations feasible again. The problem lies in the fact that most of these mines are now flooded and information on their status and layout is, in many cases, either not actualised or even lost. UNEXMIN’s solution proposes a new robotic system, made by three robots, to autonomously explore and map flooded mines to obtain these data.

3 Development

Spanning from the beginning of the project on February 2016 until February 2019, the UNEXMIN robotic platform saw a series of different stages of evolution. First, specifications of the system, that are a combination of internal and external stakeholder requirements (e.g. limitations in robotic functions and technology within the application environment, end user requirements for the system). Seconding this initial phase, work focused on validating and simulating robotic functions, designing, testing and adapting of instrumentation units, with focus on the scientific instrument array, developing mine perception, navigation, 3D mapping and exploration tools and developing post-processing and data analysis tools. These is a continuous phase, as the UNEXMIN team is focusing on constant testing and improvement. The third phase is the construction of the actual platform. The first of three prototypes, the UX-1a robot (Figure 1, right) – was assembled in April 2018 with extensive real environment testing in April/May 2018 (Figure 1, left). Currently, the second UX-1 robot, UX-1b, is being assembled. Work will proceed in May 2019 with the assembly of the third robot of the multi-platform, UX-1c.

Fig. 1: The current UX-1a robot (left) and its testing in a pool environment prior to the first field trials (left).

UX-1a has already been tested in the two first trial sites from the four selected (in order of occurrence): Kaatiala mine, Finland (June 2018), Idrija mine, Slovenia (September 2018), Urgeirica mine, Portugal (March and April, 2019) and Ecton mine, UK (May 2019). The remaining two robots will be tested in the field whenever they are ready: UX-1b will be tested in the Urgeirica mine and UX-1c will be tested in Ecton mine.

Besides the assembly of the second robot, the team is currently working on post-processing and analysing the data obtained from the Kaatiala and Idrija tests to produce 3D models and other tools of interest to be used for educational and cultural purposes, in line with the requests from the project’s internal stakeholders. At the same time, testing to implement autonomy is ongoing.

The next steps in the development process will include finalising the production and assembly of robots UX-1b and UX-1c and complete the field testing at the Urgeirica and Ecton mine trial sites. The biggest focus will be put on exploring and mapping the entire flooded section of the Ecton mine, that nobody has seen for more than 160 years. By the end of the project, in October 2019, the UNEXMIN team will have proved the operability of the robotic system in different sites with different conditions, making a strong case for the exploration platform.
4 UX-1 characteristics and instrumentation

The application environment to which the UX-1 robots will be subjected constrains basic robotic functions, the dimensions and mass of the robot, and data collection. Also, environmental characteristics restrict both the type and amount of equipment that is able to be mounted onto the UX-1 robot. UX-1 has the following characteristics:

- A spherical shape with a diameter of 60cm
- A maximum operation depth of approximately 500m
- A total weight around 112Kg
- A power consumption between 250-400W
- A working speed of 1-2Km/h
- Autonomy up to 5 hours per mission
- Neutral buoyancy

UX-1’s characteristics arise from a combination of stakeholder needs and desires, the conditions observed in underground flooded mines and the robotic functions needed for underwater investigations. There is a need for a trade-off in the equipment’s quality/quantity/size, as both basic functions and scientific equipment need to be considered and limitations in the surveyor size are observed. The robot’s needed abilities to perform basic tasks include unobstructed movement, autonomy, mapping and environmental awareness. A set of robotic subsystems (and respective linked components) and scientific instrumentation allow the robot to perform in the application environment.

Six subsystems are defined and include 1) the perception system, used to measure environmental conditions and obtain information for navigation and guidance, 2) the propulsion system, needed for movement, 3) the ballast system, needed for buoyancy control, 4) the pendulum, responsible for changes in the pitch angle, 5) the power supply system, consisting of five sets of batteries and 6) the computer, necessary for the robot’s operation. These subsystems comprise components such as acoustic cameras, SONAR (Sound Navigation And Ranging), thrusters, laser-scanners, computer, rechargeable batteries, pendulum, buoyancy control system and a protective pressure hull.

Due to the limitations in size and space, power supply, high-precision navigation and positioning and control, obtaining geological data through direct methods (i.e. sampling) is impossible. Therefore, the UX-1 robot employs mineralogical, water sampling and geophysical methods and instrumentation to obtain valuable data (Figure 2). Scientific instruments were specifically designed and built to measure pH, pressure, temperature, conductivity and other geochemical parameters, magnetic fields and gamma radiation levels. The geophysical tools enable sub-bottom profiling and multispectral and UV fluorescence imaging. Water samples can be collected with the water tank. Together, this array of scientific instrumentation retrieves geoscientific data on water geochemistry, geophysical imaging and mineralogical identification during missions.
The capabilities of the robotic system as well as its instrumentation are object of precise testing and study during the trials (Figure 3).

Fig. 3: Multispectral camera testing during the Kaatiala field trials.

5 Future applications

Besides the use of the robotic system on exploration and mapping of flooded mines, to what the system is currently directioned as it is the main aim of the project, this technology can be used as well in other application environments. Other sectors where the UX-1 system can be applied include security, water management and maritime wildlife control, for example. The project team is currently considering the following applications for its system (with some adaptations in instrumentation required for some) while cross-fertilisation with other sectors is also being studied:
- Providing data on mineral deposits and opening new exploration scenarios for raw materials;
- Drafting more informed and successful drilling plans for mineral exploration;
- Giving access to new geological data necessary to understand Earth’s processes, helping to
  improve fields within the geosciences;
- Underwater exploration in highly hazardous or dangerous areas (nuclear accidents, toxic
  spills, surveying of unstable underwater environments - after earthquakes or similar etc.);
- Offering supporting data to other sectors: archaeology, civil engineering, energy efficiency or
  resource management;
- Monitoring the integrity of civil engineering structures, including water pipelines;
- Environmental monitoring, including monitoring of wildlife (such as fisheries);
- Cave exploration and tourism planning development.

To allow future exploitation of the system outside the scope of the UNEXMIN project, the consor-
tium creates a company that holds the rights for the robotic system and that will use the multi-
robotic platform to service the different markets identified. This company will continue to pursue
further development of the technology, including new instrumentation and modifications on the
UX-1 series (e.g. bigger working depth, smaller version for even more confined spaces) to better
serve the market needs.

6 Conclusion

UNEXMIN’s robotic platform is making a big advancement in the field of underwater exploration
technology in a new application environment. The first UX-1a robot has been developed and tested
already in two trials sites. UX-1b and UX-1c are in the construction on assembly phases. Further
development of mine perception, navigation, 3D mapping and exploration tools, as well as post-
processing and data analysis tools is ongoing at the same time. The technology will be still tested
and improved in the Urgeiriça and Ecton mines until the end of the project lifetime. The technology
developed in UNEXMIN will be able to retrieve important geological and spatial data that cannot
be currently obtained in any other way, data which will have an impact in applications across geo-
sciences, engineering, and resource management.

7 Acknowledgement

The UNEXMIN project has received funding from the European Union’s Horizon 2020 research
and innovation programme under grant agreement No 690008.
8 References


SOLSA-Field tests: indispensable for reaching SOLSA Goals

Monique Le Guen, Beate Orberger

SOLSA CONSORTIUM

ABSTRACT:

The SOLSA field tests were performed in order to evaluate the different instrumental parts of the SOLSA EXPERT system, SOLSA DRILL and SOLSA ID 2A (core scanner: RGB, profilometer, hyperspectral cameras (VNIR, SWIR)), ID 2B (combined analyses: XRF-XRD-Raman spectroscopy), and part of the data architecture and software, under field conditions in an on-line-on-mine-real-time workflow.

The field tests were performed in the bauxite mine of the SODICAPEI-VICAT company (Villeyverac, SouthernFrance). This site was chosen for its similarities with nickel laterite profiles. The tests of different parameters allow modifying and adapting specific compounds of the SOLSA Expert system until the end of the project in February 2020.

For the SOLSA DRILL, two bore holes were drilled at about 36 and 31 m, respectively. The lithologies vary from clays, clayey siltstone, siltstone and very fine sandstone. All lithologies contain variable amounts of iron oxy-hydroxides and carbonates. Micro-nodules of calcite are also present. A large part of the clayey material and siltstone hosts swelling clay minerals (mainly montmorillonite).

Different parameters were tested during sonic drilling: (1) wireline for bore holes deeper than 3 m. (2) special split liners; (3) different types of core catchers; (4) different types of drilling fluids.

The SOLSA ID2A (core scanner: RGB camera, profilometer, VNIR and SWIR cameras) as mounted for the tests in a minivan, was affected by vibrations. However, in field, 1 m of core was scanned in about 15 min (leading to 40 m in a 10 h shift per day). Individual data (RGB, profilometer, hyperspectral data) was treated on field after scanning. The XRF spectrometer was not yet mounted due to the lack of approved protection. On-line-real-time data interpretation was not yet achieved.

For SOLSA ID 2B, the sample powder preparation was tested by micro mill (average grain size < 10 μm) and satisfactory results were achieved with our protocol.

The SOLSA ID 2B system was tested using at that time only XRF-XRD combined analyses. The instrument gave satisfactory results for the 15 analyses.
The SOLSA Data architecture was revised, data from DRILL and IDs were connected, data flows were tested and software upgrade and upset will be done based on these results.

Performing field tests at this stage of the project was a good decision, it merged all partners for 15 days in the field for discussions, experiments and data evaluation. The data evaluation is in progress, and will be used for the final development.
Remote Reading Instrumentation Requirements for Longwall Automation in Underground Coal Mines

Charles Sweeney¹, Nathan Owen²

¹ Anglo American, ² NOME Services

ABSTRACT:

Australia’s coal mining industry accounts for 27 per cent of total revenue for the mining industry as a whole, and approximately 24 per cent of employment. Longwall mining accounts for around 90 per cent of Australia’s underground coal production. The mining industry continues to improve conditions for mine workers, striving for zero harm. Research and development into real-time monitoring and longwall automation is one way that the industry is seeking to improve safety in underground longwall mines.

Real-time monitoring around the retreating longwall face reduces the number of required tailgate inspections, leading to a reduction in exposure of personnel to potential adverse tailgate environments (i.e. gas, dust and strata). Reduced tailgate inspections has also been proven to lead to increased production.

Advances in longwall automation include specialized remote guidance technology, used to continuously steer the longwall equipment from anywhere with internet availability. However, it has been recognized that an automated longwall face will not be able to recognize all changing conditions and that real-time monitoring advances, as well as skilled operators, will aid in identifying changing conditions.

Remote Reading Tell-tales (RRTT) monitor roof movement in the gateroads adjacent to the retreating longwall face. Roof movement, and associated longwall weighting events monitored from the hydraulic roof supports, identifies times when mining should not stop for scheduled maintenance. The requirement to keep cutting, particularly when weight is being thrown onto the longwall face from the cantilevering strata above the goaf, reduces the potential for roof falls in the tailgate/Main gate.

Furthermore, longwall automation provides:

- Improved safety conditions for longwall mining equipment operators (reduced exposure to dust and gas)
- Increased productivity, which delivers an economic benefit

Anglo American Australia has recently taken its first automated longwall shear from the surface of one of its underground coal mine (2018), with the intent to transition all of its
underground longwall operations to being fully automated in the future. All Anglo American underground coal mines within Australia currently employ Remote Reading Tell-tales (RRTT). These are typically installed a minimum of 100m ahead of the retreating Longwall face. Monitoring roof movement, particularly in the Tailgate, allows for an immediate response to tailgate instability – vital for ventilation. With a pending change to longwall automation, the continued use of RRTT’s will contribute greatly to its successful implementation.
Geochemical mapping of drill core samples using a combined LIBS and XRF core scanning system

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Spectral Industries, Delft, The Netherlands

ABSTRACT:

A prototype of a LIBS-XRF drill core scanner was developed through a collaboration between Avaatech B.V. and SPECTRAL Industries B.V. This core scanner was tested on a drill core sample of a polymetallic sulphide ore originating from the historic Reiche Zeche mine in Freiberg, Germany. Comparing the LIBS and XRF data showed that both techniques produce similar results for all the major elements of which the sample is composed. Differences between the results of LIBS and XRF were also observed, which were attributed to differences in the size of the measured surface area, signal to noise ratio, and detection limits of LIBS and XRF. Additionally, XRF cannot be used to detect light elements such as oxygen or carbon, while these elements can be detected with LIBS. Another advantage of the LIBS technique is that the data acquisition speed is much higher. This is especially useful when drill core scanning is applied in large mineral exploration projects in which hundreds of kilometres of drill core samples are produced. Drill core sections that are of special interest can be further investigated using XRF, which may provide a higher precision for determining the content of certain trace elements such as arsenic.
1 Introduction

Core drilling is often used in the exploration for mineral resources and other geological studies to obtain information about the Earth’s subsurface. Analysis of the obtained drill core samples is traditionally performed through visual inspection and laboratory analyses, which are generally time consuming and expensive. Alternatively, sensors can be used to collect mineralogical and geochemical data at much higher speeds and lower costs.

Drill core scanners are systems that use a certain sensor or combination of sensors to gather information on drill core samples. Sensor techniques that are commonly used for drill core scanning are digital imaging and near-infrared (NIR) and short-wavelength infrared (SWIR) hyperspectral imaging. These techniques provide information on a material’s visible properties and the occurrence of specific minerals (Thompson et al., 1999; Dalm et al., 2018). However, ore minerals can often not be detected, and no information is provided on the chemical composition of samples. This while the concentration of ore minerals in the rock is usually the most important parameter in mineral exploration studies.

Laser-induced breakdown spectroscopy (LIBS) is a sensor technique that provides information on a material’s chemical composition. It utilizes a pulsed laser beam to ablate a small amount of material on the surface of a sample and break it down into a plasma consisting of atoms, ions and free electrons. When the plasma cools down it emits electromagnetic radiation because the free electrons release energy in the form of photons when they fall back into atomic or ionic orbits (Radziemski & Cremers, 2006). The wavelength at which these emissions are produced depends on the specific atom or ion in which the electron is captured, and the intensity of the emission is related to the concentration of that atom or ion. The composition of a material can therefore be determined by using a spectrometer to measure the radiation that is emitted by the laser-induced plasma.

X-ray fluorescence (XRF) is another technique that can be used to determine chemical composition. No plasma is produced with XRF, but electrons in the inner orbitals of atoms are ejected from their orbit by bombarding them with high energy X-rays. Electrons in higher orbitals will subsequently fall into the hole that is left behind and release energy in the form of photons (Beckhoff et al., 2007). As with LIBS, the intensity and wavelength position of the photon emissions depend on the type of atom and its concentration in the sample. The composition of the sample can therefore be determined by measuring these emissions with a spectrometer.

One of the main differences between LIBS and XRF is that LIBS deals with emissions of the outer-shell electrons, while XRF deals with emissions of inner-shell electrons. For certain transition metals many different energy levels exist in the outer-shells on which electrons can be captured. When these transition metals occur in relatively high concentrations, their emissions may dominate the LIBS spectrum and occlude emission lines of other elements. The XRF technique does not suffer from this phenomenon because a lower number of inner-shell energy levels exist.

The disadvantage of the XRF technique, however, is that light elements are more difficult to detect because the inner-shell energy levels of these elements are relatively low and have a low penetrating power (Beckhoff et al., 2007). As a result, the emissions from light elements are more quickly absorbed by the surrounding air. This problem can be partly overcome by measuring in an environment where the air is replaced by helium or argon. However, detecting elements lighter than sodium
also requires a special configuration of the XRF sensor (Beckhoff et al., 2007). Hydrogen, helium and lithium cannot be detected with XRF at all.

A comparison was made between LIBS and XRF to investigate if a combination of both techniques offers unique opportunities for fast drill core scanning in the field. This comparison is based on tests with the LIBS-XRF core scanner prototype that was developed through a collaboration between Avaatech B.V. and SPECTRAL Industries B.V.

2 Experimental

Figure 1 shows a photo of the LIBS-XRF core scanner prototype that was tested in this study. This prototype was developed by integrating the LIBS instrument of SPECTRAL Industries into Avaatech’s 4th generation XRF core scanner. Table 1 presents the specifications of the core scanner and the LIBS and XRF instruments.

The LIBS-XRF core scanner prototype was tested on a 28 cm long drill core sample of a polymetallic sulphide ore originating from the historic Reiche Zeche mine in Freiberg, Germany. Around 800 years ago this ore was mined as a resource for zinc, lead, copper, and silver. The ore is mainly composed of the minerals pyrite, sphalerite, galena, chalcopyrite and arsenopyrite. Gangue minerals include calcite, siderite, and quartz (Bayer, 1999).

The LIBS and XRF measurements were acquired along the same line in the downhole direction of the sample. The surface area on which the XRF measurements are performed can be adjusted by changing the slit size of the instrument. The slit size was set to 0.2 mm downhole and 2 mm crosscore for the test measurements. The spatial resolution of the XRF measurements was set at 0.2 mm. The range of elements that can be detected with XRF depends on the excitation energy that is used, which relates to the voltage that is applied to the X-ray tube. The XRF data was acquired by making one scan while operating the X-ray tube at 10 KV and one scan while operating at 30 KV. For each XRF spectrum an integration time of ten seconds was used. The total time needed to acquire the XRF data was ten and a half hours.
Table 1: Specifications of the LIBS-XRF core scanner prototype

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<td>Slit system</td>
<td></td>
</tr>
<tr>
<td>Downcore resolution</td>
<td>0.1 - 10 mm</td>
</tr>
<tr>
<td>Crosscore resolution</td>
<td>2 - 12 mm</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LIBS instrument</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Laser</td>
<td></td>
</tr>
<tr>
<td>Type</td>
<td>Litron Nano SG 150-10</td>
</tr>
<tr>
<td>Wavelength</td>
<td>1064 nm</td>
</tr>
<tr>
<td>Pulse length</td>
<td>4 - 6 ns</td>
</tr>
<tr>
<td>Max pulse energy</td>
<td>150 mJ</td>
</tr>
<tr>
<td>Max repetition rate</td>
<td>10 Hz</td>
</tr>
<tr>
<td>Spot size</td>
<td>100 µm</td>
</tr>
<tr>
<td>Spectrometer</td>
<td></td>
</tr>
<tr>
<td>Type</td>
<td>SPECTRAL Industries IRIS echelle spectrometer</td>
</tr>
<tr>
<td>Detector</td>
<td>Deep-UV sensitive CMOS</td>
</tr>
<tr>
<td>Spectral range</td>
<td>180 - 800 nm</td>
</tr>
</tbody>
</table>
The surface area on which the LIBS measurements were performed was around 0.1 mm in diameter and the spatial resolution of the measurements was 0.12 mm. The LIBS measurements were gated using a delay of 2.4 µs between plasma generation and data acquisition. LIBS spectra were acquired at 10 Hz using an integration time of 98 µs. The laser power was set at 15 mJ per pulse. The total time needed to acquire the LIBS data was three minutes and twenty seconds. LIBS measurements were performed while flushing the instrument with argon to obtain representative data on elements occurring in the atmosphere such as oxygen and carbon.

Processing of the LIBS and XRF spectra was performed by first subtracting the baseline from the spectra. Subsequently, characteristic atomic emission lines were identified and a voigt profile was fitted to the peaks in the LIBS and XRF spectra. The line intensity of the elements was determined by calculating the area of the voigt.

3 Results

Figure 2 presents the line intensities of selected element peaks in the measured LIBS and XRF spectra versus the position of the measurement. Element line intensities shown in black are based on the LIBS data and those shown in blue are based on the XRF data. Figure 2 also shows a photograph of the sample. The red rectangle on this photo indicates the line along which the LIBS and XRF spectra were measured.

All the element line intensities shown in Figure 2 are scaled to the same range and absolute intensities between elements can be different. The relationship between measured line intensity and actual element concentration is unknown for both LIBS and XRF and may be non-linear. Both techniques are subject to chemical matrix effects, which is the phenomenon in which the line intensity of an element is influenced by the other constituents of the sample. Additionally, line intensities may depend on physical matrix effects such as the surface roughness, hardness, density, grain size, or crystallinity of the material that is measured (Harmon et al., 2013; Potts & West, 2008). The influence of chemical and physical matrix effects in LIBS may be different than those in XRF.

Figure 2 shows that the LIBS data appears noisier than that of XRF. This is partly caused by instrumental noise because LIBS is subject to signal intensity fluctuations resulting from an uneven energy distribution between laser pulses and physical matrix effects (Harmon et al., 2013). However, most of the noisy appearance is likely due to the relatively small surface area that is measured with LIBS in combination with the occurrence of fine-grained minerals in the sample. This means that small-scale heterogeneity of the drill core sample itself is the main reason for the noisy appearance of the LIBS data. The influence of small-scale heterogeneity on the XRF data is lower because the surface area that is measured with XRF is larger. Compositional variations due to the occurrence of fine-grained minerals in between minerals with a larger grain size are therefore averaged out.
Figure 2: LIBS and XRF results of scanning a polymetallic sulphide ore sample. The pink bands indicate the position of quartz / calcite veins.
Figure 2 does not present any LIBS data for arsenic and XRF data for oxygen and carbon. This is because oxygen and carbon are light elements that cannot be detected with XRF and arsenic emissions were not observed in the LIBS spectra. For the elements that were detected with both LIBS and XRF, the measured line intensities presented in Figure 2 show a similar trend. However, differences between the results of LIBS and XRF can also be observed. Most of these are likely caused by differences in the surface area that is measured. Especially the field of view of the XRF instrument in the crosscore direction is much larger than that of the LIBS instrument (2 vs. 0.1 mm).

The most dominant mineralogical feature that can be observed from the data presented in Figure 2 is the occurrence of the white veins that can be seen in the photograph. The positions of two of these veins are highlighted in pink. The LIBS data shows that the white veins can be identified by using the line intensity of oxygen. This can be explained by the fact that the white veins are mainly composed of quartz (SiO₂) and/or calcite (CaCO₃), while most other minerals that occur in the sample are sulphides (pyrite (FeS₂), sphalerite (ZnS), chalcopyrite (CuFeS₂), galena (PbS)). Based on the line intensities of Si and Ca, it can also be derived that the highlighted vein on the left mainly consists of calcite, while the one on the right mainly consists of quartz. The source of carbon in the quartz veins is somewhat unclear but might result from minor occurrences of other carbonates or small fluid inclusions containing CO₂. Fluid inclusions in quartz are common in the type of deposit from which the drill core sample originates.

The second mineralogical feature that can be seen in Figure 2 is the occurrence of pyrite (FeS₂) versus sphalerite (ZnS) and chalcopyrite (CuFeS₂). In the left half of the sample pyrite is the most abundant mineral and occurrences of sphalerite and chalcopyrite can be identified from an increase in the line intensity of zinc or copper and a decrease in the intensity of iron. Occurrences of sphalerite and chalcopyrite seem to be spatially associated with each other since the line intensities of zinc and copper show similar trends. In the right half of the sample, sphalerite is more abundant and the line intensity of iron is lower than in the left half of the sample. The iron in this part of the sample is probably contained by chalcopyrite, although sphalerite can also contain iron (Awadh, 2009). It is also possible that relatively small pyrite grains occur in between those of sphalerite and/or chalcopyrite and that the measured iron is from a mixture of several minerals. This cannot be confirmed with either LIBS or XRF since measured line intensities may not be linearly related to element concentrations. A different analytical method is therefore required to confirm the source of the iron.

The third mineralogical feature that can be seen in Figure 2 is the occasional occurrence of galena (PbS) and arsenopyrite (FeAsS). Galena can be identified from the relatively high line intensity of lead and arsenopyrite from that of arsenic. Figure 2 shows significant differences between the results of LIBS and XRF for lead. A possible explanation for this is that the grain size of galena is relatively small. This is indicated by the fact that high line intensities for lead in the LIBS data occur over narrow ranges. Furthermore, the XRF data often still shows a small increase in the line intensity of lead at positions where the LIBS intensity of lead is high. When relatively small galena grains occur at the positions where a high intensity for lead is measured with LIBS, these will be averaged out in the XRF measurements because the surface area that was measured with XRF is larger.

Differences in the measured surface area can also create situations in which galena grains occur within the area measured with XRF, but not within the area measured with LIBS. This explains why the XRF results can show high line intensities for lead while LIBS does not. The same could apply
to the arsenopyrite, which explains the absence of emission lines of arsenic in the LIBS data. However, it is also possible that the concentration of arsenic is below the detection limit for LIBS. The detection limit varies between elements and detection limits of LIBS can be different than those of XRF.

Finally, it was mentioned that the ore deposit from which the drill core sample originates was historically also mined for silver. With the XRF instrument silver could not be measured because the used slit contains silver, which interferes with the detected line intensities for this element. From the LIBS data no emission lines of silver were observed, but many of these lines also overlap with those of iron. It is also possible that the drill core sample used in the test was taken from a part of the deposit in which no significant amounts of silver occur.

4 Discussion

The core scanning system used in this study was based on Avaatech’s 4th generation XRF core scanner on which the LIBS instrument developed by SPECTRAL Industries was integrated. XRF is a well-established analytical technique with applications in many different fields. It is often used for quantitative analyses, which is possible through calibration of the instrument with calibration standards. The same approach can be used to calibrate LIBS instruments. It is therefore possible to calibrate the LIBS-XRF core scanner in order to extract full quantitative information from each measurement instead of the semi-quantitative results displayed in Figure 2. However, this does require a fairly large range of calibration standards that represents the mineralogical variability of the deposit in order to account for the matrix effects that are usually associated with LIBS and XRF.

Extracting quantitative compositional information from individual LIBS or XRF measurements might not be needed for drill core scanning applications. The results in this paper showed that mineral occurrences could be inferred from the LIBS or XRF data (minerals associated with the deposit were known). This means that machine learning and multivariate classification can be used to classify measured spectra on the occurrence of certain minerals or mineral mixtures. By taking measurements at a sub-mm spatial resolution it is then possible to quantify the mineralogy on intervals in the order of tens of centimetres by counting the number of measurements in which a certain mineral was identified. For the sample shown in Figure 2 for example, this approach would show a higher concentration of Zn- and Cu-bearing minerals over the 140-240 mm positions compared to the 0-100 mm positions. If LIBS or XRF drill core scanning is applied to hundreds of meters of drill core from an ore deposit, this approach can likely be used to accurately delineate higher and lower grade ore zones and distinguish different ore types. Furthermore, relatively small veins and fractures can be identified which may provide a better understanding of the geological processes that are associated with mineralization. This can be used to improve deposit models and better target physical sub-sampling for geochemical assay.

The main advantage of LIBS over XRF for drill core scanning is that the data acquisition speed of LIBS is much higher. The LIBS instrument that was used in the test can acquire LIBS spectra at a frequency of 10 Hz, which means that scanning a meter of drill core at 0.1 mm resolution takes about seventeen minutes. However, measurement frequencies of 1 KHz are also possible for LIBS applications (eg. Rifai et al., 201), which would reduce the scan time for a meter of drill core to
only ten seconds. The XRF instrument that was used in the test needs at least ten seconds for a single measurement and longer measurement times might be needed to acquire data on elements occurring in low concentrations. Furthermore, the range of elements that can be detected depends on the excitation energy that is used, which relates to the voltage that is applied to the X-ray tube. To obtain accurate information on the full range of elements, XRF measurements using three different excitation energies are needed. Additionally, the XRF instrument needs to be in contact with the sample during the measurement and about six seconds are needed to relocate the instrument between measurement locations. This means that scanning a meter of drill core at 0.1 mm resolution by using three excitation energies and ten seconds of measurement time takes almost six full days. However, this can be significantly reduced by decreasing the resolution and number of excitation energies at which the measurements are performed. Scanning a meter of drill core at 1 cm resolution using only one excitation energy can be done within thirty minutes.

Another advantage of LIBS is that it is possible to detect light elements. Especially the ability to detect carbon, oxygen and sulphur provides significant advantages for drill core scanning since these elements can be used to distinguish between mineral groups such as oxides, carbonates, sulphates and sulphides. Additionally, the ability to detect hydrogen could potentially be used to characterize mineral hydration, which may be relevant when investigating ore deposits associated with hydrothermal alteration.

An advantage of XRF over LIBS is that there is a lower chance that the emission lines of an element of interest overlap with the lines of other elements. As was mentioned in the introduction, certain transition metals produce many different emission lines in a LIBS spectrum which may prevent the accurate detection of other elements. Additionally, signal to noise ratios and detection limits of XRF and LIBS can be different. This means that for certain elements XRF might provide better results than LIBS and vice versa.

5 Conclusions

Testing the LIBS-XRF core scanning prototype on a drill core sample of a polymetallic sulphide ore showed that LIBS and XRF produce similar results for all the major elements of which the sample is composed. By using either the LIBS or XRF data it was possible to identify and map the occurrence of economically important minerals that can be used to characterize ore grade. Differences between the results of LIBS and XRF were also observed, which can be explained by differences in the size of the measured surface area, signal to noise ratio, and detection limits of LIBS and XRF. Additionally, light elements such as oxygen or carbon that were detected with LIBS could not be detected with XRF.

Whether it is better to use LIBS or XRF for geochemical mapping of drill core samples depends on the specific goal of the application. This is mainly due to the detection limits that are associated with each technique, which depend on the mineral matrix in which an element resides (Radziemski & Cremers, 2006; Kadachi & Eshaikh, 2012). As was shown in this study, it is possible to combine LIBS and XRF in drill core scanning to allow a more complete characterization of the composition of samples.
The LIBS-XRF core scanning prototype is a transportable unit that can be operated in the field. LIBS can be used to rapidly scan drill cores because of the relatively high scanning speed that can be achieved. This is especially advantageous when drill core scanning is applied in large mineral exploration projects in which hundreds of kilometres of drill core samples are produced. Drill core sections that are of special interest can be further investigated using XRF. Especially for determination of the content of certain trace elements such as arsenic, XRF may provide a higher precision than LIBS.

6 Acknowledgement

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REFERENCES


Evaluation of sensor technologies for on-line raw material characterization in “Reiche Zeche” underground mine - outcomes of RTM implementation

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ABSTRACT:

The increasing advances in sensor technology have resulted in greater availability of sensor data for a wide range of applications. One such application is raw material characterization in mining operations. Sensor technologies operate over certain range of the electromagnetic spectrum and provide information on several aspects of material properties. The sensitivity and the material properties the instrument detects and measures varies from sensor to sensor. The purpose of this study was to synthesize and evaluate the use of sensor technologies for characterization of a polymetallic sulphide deposit in “Reiche Zeche” underground mine. This paper discusses the material characterization methodology using sensor technologies, demonstrates how it fits within the Real-Time Mining (RTM) framework, identifies the interface for both software and hardware requirements and defines the gaps and limitations of application of sensors. It provides a brief overview of the use of sensor and data fusion for material characterization to convey a high-level context in raw material characterization. The sensor technologies considered in this study include RGB imaging, visible–near infrared (VNIR), short wave infrared (SWIR), mid-wave infrared (MWIR), long-wave infrared (LWIR) and Raman spectroscopy.

The required information from sensor data in mining operations is not limited to grade control applications. Information on co-occurring minerals or elements are also important for definition of requirements in mineral processing, to identify indirect proxies of elements/minerals of interest, to understand the formation of minerals, to define requirements for blasting parameters, to improve safety and to define requirements for environmental monitoring of toxic material. In view of these points, there is a need for combinations of sensors to achieve a near complete description of material composition and properties. The methodological approaches developed for information extraction from each sensor data and fused data are presented. This includes both direct mineral fingerprinting and indirect proxies using spectral data. The efficient sensor data processing methods and the acquired results from the use of individual sensor and the fused data are summarized. Overall, the acquired results from the use of each sensor technology and the data fusion approach significantly contributed to an improvement of data quality and illustrate the effi-
ciency of use of sensors in the mining industry. However, some of the observed limitations include lack of system robustness, a need for test case specific mineral libraries, the need for development of an integrated principled tool for efficient data collection, processing and knowledge generation. Going forward, automated material characterization is possible with robust system design (exemplified by portable and ruggedized system) and efficient software (test case specific mineral libraries) that can be developed using a combined sensor signal.

Keywords—sensor technologies, data fusion, material characterization, on-line data, mining

1 Introduction

Sensor technologies that produce high-throughput multi and megavariate data are advancing. Sensors derived data are in current use in a wide range of applications. Raw material characterization in mining operations is one application area. Sensor technologies measure different aspects of material properties. Material property is a broad term that includes physical, chemical, optical, mechanical and atomic properties. Fundamental understanding of material characteristics is crucial in selecting suitable sensor solutions for operational decision making using raw material characterization. In addition, the selection of sensors for a specific application requires knowledge of sensor parameters. These parameters include operating wavelength range, spatial resolution, spectral resolution, accuracy, precision, sensors field of view (spot size), robustness for environmental conditions (such as vibration, humidity and dust), detection limit and depth of penetration (e.g surface or volumetric measurements).

The operating wavelength range of a sensor is the window of the electromagnetic spectrum on which the given sensor operates. Spatial resolution specifies the pixel size of an image that provide details or the smallest addressable element the image holds (the distinct detail in the image). Spectral resolution is a measure of sensor ability to resolve spectral features and bands into separate components (width of spectral band). Finer spectral resolutions enable the higher resolution spectral characteristics of the targets to be captured by the sensor. Accuracy is a measure of the closeness of a result to the true or known standard value. Precision refers to the reproducibility of multiple measurements. Sensor field of view or spot size refers to the size of the measured area of a single measurement. Robustness of sensor systems for harsh environmental conditions (e.g vibration, humidity and dust) is important for in-situ applications (e.g for underground applications). Detection limit of a sensor is the lowest quantity of a substance that can be detected by the system with a general confidence level of 99%. It is a key parameter for application of sensors in low-grade mines. Depth of penetration is the depth light or electromagnetic radiation can penetrate into a material.

The field of view or the extent of observable scene of sensors differs from technology to technology. Thus, some technologies produce point data, while the others produce image data. For example, the imaging technologies cover a larger area of a target and provide a 2D image that shows the spatial and spectral distribution of entities under investigation. Whereas, the point techniques cover a very small area (spot size) and generate point data, discrete unit of information that is acquired from a single spot (though the spot size varies from instrument to instrument). Depending on the techno-
logy, the point data are spectra which consist of wavelength and reflectance or intensity information. Based on the output data type, sensor technologies are divided into point spectroscopies and imaging spectroscopies.

Crucial information from sensor derived data are applications dependent. For example, the key material properties (geological attributes) in mining operations include mineralogy, geochemistry, fragmentation and ore geometry. Knowledge of these properties plays a key role in supporting effective decision making in mining operations. Thus, improves the economic and environmental benefits. This paper presents the use of RGB imaging, visible–near infrared (VNIR), short wave infrared (SWIR), mid-wave infrared (MWIR), long-wave infrared (LWIR) and Raman technologies for polymetallic sulphide ore characterization, highlights the developed methodological approaches for knowledge generation, addresses the opportunities with sensor combinations and defines the gaps and limitations for future research works. The sensor technologies are described in Table 1.

Table 1: Sensor technologies operating wavelength range, the material properties the systems measure and the geological attributes that can be derived from the sensors signal

<table>
<thead>
<tr>
<th>No.</th>
<th>Sensor</th>
<th>Operating Wavelength range (µm)</th>
<th>Material Properties/Type of energy transfer</th>
<th>Geological attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RGB Imaging</td>
<td>0,4 - 0,7</td>
<td>Reflection</td>
<td>Mineralogical</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Texture (Fragmentation)</td>
</tr>
<tr>
<td>2</td>
<td>Hyperspectral Imaging (VNIR)</td>
<td>0,4 - 1,0</td>
<td>Reflection\Absorption</td>
<td>Mineralogical</td>
</tr>
<tr>
<td>3</td>
<td>Hyperspectral Imaging (SWIR)</td>
<td>1,0 - 2,5</td>
<td>Reflection\Absorption</td>
<td>Mineralogical</td>
</tr>
<tr>
<td>4</td>
<td>Mid Wave Infrared (MWIR)</td>
<td>2,5 - 7,0</td>
<td>Reflection\Absorption</td>
<td>Mineralogical</td>
</tr>
<tr>
<td>5</td>
<td>Long Wave Infrared (LWIR)</td>
<td>7,0 -15</td>
<td>Reflection\Absorption\Emission</td>
<td>Mineralogical</td>
</tr>
<tr>
<td>6</td>
<td>RAMAN</td>
<td>0,2 -1,4</td>
<td>Scattering of radiation</td>
<td>Mineralogical</td>
</tr>
</tbody>
</table>

2 Study sites

The Reiche Zeche underground mine located in the Freiberg district, eastern Erzgebirge, Germany, served as the case study area. The deposit is characterized by polymetallic vein type mineralization formed by two hydrothermal mineralization events of Late-Variscan and Post-Variscan age (Seifert 2008). The Late-Variscan mineralization event dominates in the central part of the mine and mineralization is rich in sulphur, iron, lead, zinc and copper. Typical ore minerals include pyrite, galena, arsenopyrite, chalcopyrite and sphalerite, along with quartz and minor carbonate gangue. Ore minerals with a smaller Cu, Zn and Fe content characterize the Post-Variscan mineralization event. This mineralization event consists of a fluorite-barite-lead ore assemblage, mainly containing sphalerite, pyrite, galena, chalcopyrite and marcasite, as well as quartz, fluorite, carbonates and barite, as gangue (Seifert 2008; Benkert et al. 2015).
2.1 The nature of materials

Measurements of rock attributes were performed both in-situ and using rock samples collected from mine face, drill core, muck pile and LHD potential sensor installation sites. Figure 1 shows sensor technologies used at each site. The samples were collected in the form of channel samples (from the mine face), rock chips samples (from muck pile and LHD) and drill core samples. The in-situ measurements were performed in the underground mine using an RGB imager.

Figure 1: Potential sensor solutions for characterization of materials at mine face, drill core, muck pile and LHD potential sensor installation sites in the mining value chain

3 Sensor technologies and test measurements

Out of the selected sensor technologies, the point technologies are MWIR and LWIR. The imaging techniques are RGB imaging and VNIR/SWIR hyperspectral imaging. In the sections that follow, the measurement results pertaining the point and imaging techniques are presented. The conventional techniques namely X-ray diffraction (XRD), X-ray fluorescence (XRF), Electron Microprobe Analyser (EMPA) and Inductively Coupled Plasma Optical Emission Spectrometry /Mass Spectrometry (ICP-ES/MS) data were used to validate the material characterization results.

3.1 Points spectrometers

3.1.1 RAMAN

Raman spectroscopy is a well-established technique that provides mineralogical information. It can be used for the identification of a wide range of minerals such as iron ore oxides, carbonates, silicate, sulphides and sulphate (Gaft et al., 2005; Griffith., 1975; White., 1975; Mernagh and Trudu, 1992). To assess the usability of the technology, two Raman spectrometers with excitation laser sources of 532nm and 785nm were considered. Measurements were performed using powder and rock samples. The acquired raw spectra were pre-processed and interpreted using RRUFF mineral library and other published works..

The 785nm laser Raman measurements resulted in defined Raman peaks for both rock and powder sample forms. However, the results obtained from the analysis of the rock samples were superior
than the powder samples measurements. Similarly, the 532nm laser Raman measurements resulted in a better signal for the measurements of rock samples than powder samples. Comparing the two excitation laser sources for the characterization of the test case materials, the 785nm laser source outperforms the 532nm laser source. This is likely due to the fact that longer excitation wavelengths are known to give less fluorescence than shorter excitation wavelength (Bumbrah and Sharma, 2016). The other possible reason could be, for non-transparent samples (e.g sulphide minerals) longer wavelength excitation laser sources penetrate deeper into the samples, thus provide better signal than the shorter wavelengths (Tuschel., 2016).

The Raman method provided good results for the identification of most of the test case minerals. Minerals that were identified using the 785nm laser source Raman system include; calcite, sphalerite, kaolinite, marcasite, pyrite and siderite. For example, Figure 2 shows sample sphalerite Raman spectra. The analysis of Raman applicability for the characterization of the test case materials was extended into usability assessment of ore-waste discrimination and elemental concentration prediction using the chemical fingerprints of the minerals. However, based on the analytical measurements of 40 sample, the correlation of the Raman signal to the elemental content of the material under investigation is very low therefore the prediction accuracy of the model is low. Similarly, ore-waste discrimination using Raman signal was not possible. The correlation of the Raman signal with the elemental and ore-waste discrimination was tested using both linear and non-linear techniques. However, neither linear nor non-linear relations could be achieved from the Raman signals. Therefore, this technique was not further considered for data fusion.

The main challenges of Raman spectra analysis include peak overlap and fluorescence effect. The former can be minimized by considering spectra decomposition techniques such as Multivariate Curve Resolution-Alternating Least Squares (MCR-ALS). The latter can be minimized by considering longer excitation wavelengths. Raman has a good potential for quantitative analysis of the identified minerals, however real-time application requires deposit specific mineral library that takes into account materials heterogeneity. The current advancement of the technology resulted in a hand-held instrumentation permitting in-situ measurements.

### 3.1.2 MWIR and LWIR reflectance

MWIR and LWIR reflectance data were analysed for ore-waste discrimination using chemometric analytical techniques. Design of Experiment (DoE) was implemented to identify the optimal inde-
dependent and combined data filtering techniques for discriminating the two classes using the MWIR and LWIR datasets. The processed data were used to make predictions about the composition of unknown samples. A series of prediction models were developed using the processed data combined with Partial least squares-Discriminant Analysis (PLS-DA). Model performance was evaluated using the calibration, validation and prediction statistics in the form of an estimated prediction error. When models were applied to the MWIR dataset, the prediction improved to 86.3% after baseline correction. After normalization of the LWIR data, an enhanced correct classification rate of 84.7% was obtained. The MWIR data alone provide sufficient information to successfully classify the samples into ore and waste.

This finding is of interest since this region of the electromagnetic spectrum is the least explored due to limited instrument development. The two techniques were successfully used to discriminate ore and waste materials, the reflectance signals of the two techniques combined with PLS-DA has a great potential for rapid automated online discrimination of ore and waste materials. The details of the methodological approach is described in (Desta and Buxton, 2018). In addition to ore-waste discrimination, the use of MWIR for Fe and a combined Pb Zn predictions was assessed. The acquired prediction accuracies are 85% and 86.7% respectively. LWIR is very well known for analysis of rock forming minerals, however using chemometric techniques the use of the technology for elemental prediction was assessed. The Fe prediction accuracy of LWIR spectral reflectance data combined with chemometric techniques was 88%. Likewise, a prediction accuracy of 73% was achieved for prediction of a combined Pb Zn concentration.

In the test case, sulphide minerals are the primary sources of the target elements (e.g Pb, Zn and Fe). However, identification of the sulphide minerals with direct mineral fingerprinting of MWIR and LWIR reflectance data is challenging, due to the weak features of the minerals in the spectra. However, data-divine approach can be used to extract knowledge from the multivariate reflectance spectra data of MWIR and LWIR techniques. For example, MWIR coupled to chemometric tools such as a PLS-DA can be used to distinguish polymetallic sulphide ore and waste materials using the spectra as chemical fingerprints of the mineralogy.

### 3.2 Imaging technologies

#### 3.2.1 Hyperspectral Imaging (VNIR/SWIR)

Hyperspectral imagers collect image data in hundreds of narrow adjacent spectral bands resulting in 3D multivariate data structures. Hyperspectral imaging is mainly used in airborne or spaceborne remote sensing application. The recent advancement of the technology resulted in laboratory based and field-based platforms (FLSMIDTH., 2017; HYSpex., 2017; Specim., 2017; Nasrullah, 2014; Schneider, 2011; Corescan., 2017). Depending on the sensor type and set-ups, hyperspectral images with very high spectral and spatial resolution can be acquired. Hyperspectral cameras operate over a wide range of the electromagnetic spectrum, the choice is application dependent. In this paper, the use of VNIR (0.4-1.0µm) and SWIR (1.0-2.5µm) hyperspectral images for the characterization of the materials from the test case using rock chips and drill core samples were assessed.
Prior to data analysis, the raw VNIR and SWIR hyperspectral images were pre-processed using normalization, spectral subsetting, spatial subsetting, spike correction and masking missing values techniques. To isolate noise from the signal, the minimum (or maximum) noise fraction (MNF) transformation was implemented in two cascaded Principal Component transformations. The inverse transformed MNF images were used to generate 2D scatter plots. The spectral prototypes (endmembers) were identified from the scatter plots. To cross check the uniqueness of the selected endmembers, Pixel Purity Index (PPI) was computed by projecting n-dimensional scatterplots onto a random vector. The collected spectral prototypes were interpreted to identify the possible minerals using spectral libraries such as USGS (Clark et al., 2003), TSG (AusSpec International Ltd., 2008) and JPL (Groves et al., 1992). Most of the unique spectra were interpreted however there are un-identified unique spectra as well. Training sets (Region of Interest - ROI) were generated using the spectrally unique pixels (endmembers). The ROI’s were used to produce mineral maps that show minerals distribution and pixel abundances using Spectral Angle Mapper (SAM). One of the advantages of SAM classifier is its insensitivity to illumination and albedo effects (Yoon and Park, 2015).

The minerals identified using the VNIR data include: the sulphides (e.g pyrite, galena, sphalerite and chalcopyrite), the ferric iron minerals (hematite and goethite) and carbonates (siderites) (Figure 3). Furthermore, mixed spectra were also observed. Whereas, the minerals identified using the SWIR data include: mica (muscovite), sulphate (gypsum), clay minerals (montmorillonite and illite), carbonates (siderite), tectosilicate (quartz), phyllosilicate (Mg + Fe chlorite), sulphide ores (just with no features and results with featureless line) and mineral mixture (e.g Muscovite + siderite) (Figure 4). The identified minerals were further validated using XRF (oxide analysis results), XRD and EMPA data. In addition, visual inspection was performed to validate the sulphide minerals identification (since most of the test case sulphide minerals are visually distinct).

Sulphide minerals are SWIR inactive thus do not exhibit features in SWIR data. However, the featureless nature of the minerals in the SWIR spectra was used as characteristic value to map ore versus waste materials (Figure 5 (b)). Thus, the technique is promising for ore-waste discrimination. The VNIR data show a great potential to detect and identify among the sulphide minerals. However, it needs careful analysis and validation since the sulphides do not show any particular absorption features. Automation of the mineral identification process might be challenging due to lack of particular absorption features of the sulphide minerals and the matrix effect owing to the mineral mixtures. However, the variation in the spectra can be accommodated by considering a training library
with wider range of mineral mixtures simulated based on the mineral compositions of the test case material. Owing to the acquired promising results of the two techniques and recent advancement of the technologies that resulted in portable hyperspectral camera (e.g Specim IQ developed by Specim., 2019) the application can be extended for in-situ application of mine face mapping in underground mine with suitable illumination source and robust system.

Figure 4: (a) a classified SWIR image of a rock sample (b) a drill core color composite SWIR image with identified minerals

Figure 5: a) A false color SWIR image (b) a classified image showing ore-waste discrimination

### 3.2.2 RGB imaging

RGB imagers characterize the reflectance property of a material and deliver 3 (red-green-blue) spectral bands often using three independent CCD sensors or using complementary metal oxide semiconductor (CMOS) technologies. RGB imagers are well-established techniques with rapid data processing capabilities. The recent advancement of the technology resulted in high speed 66000 fps and 7.5 µm pixel size RGB cameras (JAI., 2019). Portable and ruggedized systems are available that the systems are ideal for embedding or surface mounting in harsh environment (e.g underground mines) applications. Tomra., 2017 revealed the application of the technology for mineral sorting (e.g sorting of talc and calcite). In this section, the use of RGB images for mapping of minerals, fragmentation analysis and ore zone delineation in the underground mine was assessed.
RGB images were acquired in-situ at the defined mine face. To cover the mine face both laterally and vertically, the images were taken from the two vertical and multiple horizontal reference locations. Ground control points (GCP’s) were marked at the mine face and the geographic coordinates of the GCP’s were collected using LIDAR scan by Mine Surveying and Geodesy team of TUB Freiberg. The collected GCP’s were used to georeference and mosaic the RGB images. The data acquisition process was controlled for illumination and distortion effects. Supervised classification was performed using training sets (groups of pixels) that represent up to five mineral types. The performances of three supervised classification algorithms namely Maximum likelihood (ML), Minimum distance (MD) and Spectral angle mapper (SAM) were compared. The classification accuracy was computed using a confusion matrix (error matrix) that compares the ground truth classes with the predicted or classified pixels at each ground truth location. For the classification of the minerals of in the test case using RGB images, ML outperforms the MD and SAM classification techniques. The details of the data acquisition process and the methodological approach developed for knowledge extraction from RGB images are presented in (Desta and Buxton, 2017).

Another potential application of RGB imaging is for fragmentation analysis. Rock fragmentation through blasting influences the subsequent crushing and grinding operations. Thus, it is essential information in the mining value chain. Rock fragmentation analysis can be performed using RGB
images. However, analysis of fragmentation using images has its own limitations. For example; under-estimation or over-estimation of particle size, shadow effect and piling effect (Kemeny et al., 1993). In this study, the fragmentation analysis results were maximized by selecting appropriate sampling locations. To avoid the shadow effect the target areas were illuminated from different sides. High quality images were used. To capture the observed grain size variability multiple images were acquired and suitable image scales were used. Multiple RGB images were taken at the muck piles (piles generated from fragmented material just next to the blasted face) and LHD locations in the underground mine. Figure 8 shows fragmentation analysis results of a muck pile image. The acquired results of the fragmentation analyses are reproducible. The algorithm detects clast sizes up to 2mm and everything below 2mm is categorized in the same grain size class. Taking in to account the blasting parameters, the result can further be used for development of models that better predict fragmentation in the test case.

![Figure 8: a) RGB image taken at the muck pile b) the size distribution curve of the image c) grain size analysis result](image)

The results from the use of RGB imaging for mineral mapping, ore zone delineation and fragmentation analysis are promising. Thus, RGB imaging can further be considered as a complementary technique. It is a simple technology with a good potential for material characterization in mining operations. Looking forward, better results are possible with better quality RGB images.

### 3.3 Data fusion

Sensor combinations are required to convey a near complete description of materials. Sensor combinations can be implemented using a data fusion approach. Data fusion is a wide ranging subject that can be applied using various techniques such as chemometrics. In chemometrics, data fusion can be realized at three levels: low-level, midlevel and high-level. Low-level fusion is data level fusion, mid-level fusion is a feature level fusion and high level fusion is a decision level fusion (Borràs et al., 2015, Doeswijk et al., 2011, Federico., 2013). The data fusion methodological approach developed in the H2020 RTM project was presented in Desta and Buxton, (2018).

Low-level data fusion was implemented using MWIR and LWIR reflectance spectra data. Using the fused data block elemental concentrations of Fe and a combined Pb-Zn were predicted. Compared to the individual techniques, the fused data block model resulted in better prediction performance. For example, the acquired prediction accuracies of the MWIR data model is 85%. LWIR is very well known for analysis of rock forming minerals, however using chemometric techniques the use of the technology for elemental prediction was assessed. The Fe prediction accuracy of LWIR spectral reflectance data combined with chemometric techniques was 88%. However, the prediction...
performance of the fused data block is 94% (unpublished results). Therefore, data fusion enhanced the prediction performances of the models.

4 Discussion

4.1 Utility of different sensor types for characterization of material from the test case

The usability of sensor technologies for characterization of the test case materials is synthesized and evaluated in Table 2. The SWOT analysis shows the potential and threats to the application of the technologies in mining operations. The table also addresses the observed strength of the sensors.

Table 2: SWOT analysis of the investigated sensor technologies for the use of material characterization and their applications in underground mining operations

<table>
<thead>
<tr>
<th>Technology</th>
<th>Strength</th>
<th>Weakness</th>
<th>Opportunities</th>
<th>Threats</th>
</tr>
</thead>
<tbody>
<tr>
<td>RGB Imaging</td>
<td>• Good for qualitative analysis</td>
<td>• Surface technique</td>
<td>• Light sources can be optimized</td>
<td>• Variable operating conditions</td>
</tr>
<tr>
<td></td>
<td>• Semi-quantification is possible with pixel count</td>
<td>• The information is limited to 3 bands</td>
<td>• Improved signal processing/image processing techniques available</td>
<td>• Can be affected by surface impurities</td>
</tr>
<tr>
<td></td>
<td>• Rapid data processing</td>
<td>• Lower reflection</td>
<td>• Applicable for visually distinct minerals</td>
<td>• Surface roughness affects the measurements</td>
</tr>
<tr>
<td></td>
<td>• Can be used in color detection and shape recognition (ore-geometry)</td>
<td></td>
<td>• Most advanced technology</td>
<td>• Dust affects the measurements</td>
</tr>
<tr>
<td></td>
<td>• Can be used for fragmentation analysis</td>
<td></td>
<td>• Ruggedized systems available</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• No actual contact is required</td>
<td></td>
<td>• Small size: ideal for embedding and surface mounting</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Non-destructive</td>
<td></td>
<td>• Potential for mineral/lithological mapping</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Indirect proxy for mineralogy/grade</td>
<td></td>
</tr>
<tr>
<td>VNIR</td>
<td>• Good for qualitative and semi-quantitative analysis</td>
<td>• The smaller the wavelength range the limited the info</td>
<td>• Developments are dynamic and advancing rapidly</td>
<td>• Environmental influence (such as water and dust) can affect in-situ measurements</td>
</tr>
<tr>
<td></td>
<td>• Can be used to distinguish between some of the sulphide minerals</td>
<td>• Surface technique</td>
<td>• Potential for sensor based sorting</td>
<td>• Mineral mixtures affect the results</td>
</tr>
<tr>
<td></td>
<td>• Imaging techniques do not require actual contact with samples</td>
<td></td>
<td>• Well established technology</td>
<td>• Least commonly used for quantitative analysis</td>
</tr>
<tr>
<td></td>
<td>• Non-destructive</td>
<td></td>
<td>• Rapid data acquisition</td>
<td></td>
</tr>
<tr>
<td>SWIR</td>
<td>• Can be used for sulphide ore and waste discrimination</td>
<td>• Processing and handling of the large volumes of data</td>
<td>• Developments are dynamic and advancing rapidly</td>
<td>• Environmental influence (such as water and dust) can affect in situ</td>
</tr>
<tr>
<td></td>
<td>• Can be used for identification of associated minerals</td>
<td>• Surface technique</td>
<td>• Most advanced technology</td>
<td>• Least commonly</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Portable instruments</td>
<td></td>
</tr>
<tr>
<td>Technology</td>
<td>Strength</td>
<td>Weakness</td>
<td>Opportunities</td>
<td>Threats</td>
</tr>
<tr>
<td>------------</td>
<td>----------</td>
<td>----------</td>
<td>---------------</td>
<td>---------</td>
</tr>
<tr>
<td>Imaging techniques</td>
<td>• do not require actual contact with the samples</td>
<td>• are emerging</td>
<td>• can be acquired</td>
<td>• used for quantitative analysis</td>
</tr>
<tr>
<td>MWIR</td>
<td>• Can be used for sulphide ore discrimination</td>
<td>• Least explored region</td>
<td>• The least explored region of the IR but with a good potential</td>
<td>• No commercial system for mineral identification</td>
</tr>
<tr>
<td></td>
<td>• Spectra showed a very good correlation with Fe, the combined Pb, Zn, SiO₂, Al₂O₃, Fe₂O₃</td>
<td>• Lack of well documented mineral library</td>
<td>• Portable instrument already available</td>
<td>• Robust system is required for underground (harsh environment) application</td>
</tr>
<tr>
<td></td>
<td>• Detection limit ~0.01%</td>
<td>• Surface technique</td>
<td>• Hyperspectral imager is developed</td>
<td></td>
</tr>
<tr>
<td>LWIR</td>
<td>• Can be used for discrimination of sulphide ore and waste</td>
<td>• Surface technique</td>
<td>• Good potential for mining applications</td>
<td>• Robust system is required for underground (harsh environment) applications</td>
</tr>
<tr>
<td></td>
<td>• Can be used for identification of rock forming minerals</td>
<td>• Detection limit ~0.01%</td>
<td>• Advanced technology</td>
<td>• Camera need robust housing</td>
</tr>
<tr>
<td></td>
<td>• Spectral signal has a good correlation with some of the test case elements thus can be used for elemental prediction</td>
<td></td>
<td>• Point and imaging spectrometers are emerging</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Detect a wide range of minerals (mainly rock forming minerals)</td>
<td></td>
<td>• Portable instruments are available</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Detection limit ~0.01%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Raman</td>
<td>• Detect a wide range of minerals</td>
<td>• Detection limit (ppm level detection is not attainable)</td>
<td>• Mobile units available</td>
<td>• Sensitive to vibration and dust</td>
</tr>
<tr>
<td></td>
<td>• Detect some of the sulphide minerals</td>
<td>• Weak in intensity compared to Infrared</td>
<td>• Both imaging and point techniques are available</td>
<td>• Conflict with fluorescent minerals</td>
</tr>
<tr>
<td></td>
<td>• Enriched spectral libraries</td>
<td>• Raman signal has a very low correlation with the elemental concentration of the test case materials</td>
<td>• Provides complementary information to infrared</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Surface technique</td>
<td>• High spatial resolution (&lt; 1μm)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Ruggedized system available</td>
<td></td>
</tr>
</tbody>
</table>
4.2 Opportunities for sensing systems in mining operations

In mining, sensors can be used for different applications. For example, sensors for machine performance monitoring, collision avoidance and material characterization. Sensors for material characterization can be utilized along the mining value chain, to provide usable data on several aspects of material under investigation. The choice of sensor for characterization of certain deposit type depends on different factors, such as sensor parameters, material type (deposit type) and operational environment. Sensor parameters are broad and discussed in Section 1. Deposit types define material properties that are relevant to sensors measurement. Operational environment is the other crucial factor to consider. For example, some environments require ruggedized systems due to the harsh environmental condition, the others require sensors with high data acquisition speed such as conveyor belt applications.

In-situ application of sensor technologies requires portable, ruggedized (that can be used under harsh mine conditions) and high speed systems. With the current innovative advancements of sensor technologies, technical solutions both in terms of instrumentation and application are emerging. For example, high speed NIR sorters that are able to detect 640000 spectra per second per meter conveyor belt with a belt speed of 3m/s are available (Robben and Wotruba, 2010), portable systems such as FTIR has ~ 2kg weight (Agilent., 2017), ruggedized systems (e.g Raman from StellarNet Inc. 2019) are evolving. Sensors with enhanced sensitivity detect minerals in lower concentration, thus improved sensitivity is essential for application of sensors in low-grade deposits.

Despite researchers indicated the benefit of the use of sensors in mining industries (Buxton and Benndorf, 2013, Goetz et al., 2009, Fox et al., 2017), the use of sensors is limited due to various factors. One of the possible reasons for the limited use of sensor technologies in mining operations is the initial investment to purchase the instrument might be higher than the benefit to be realized. Advancement in sensor technologies has resulted in simplified design and low cost systems, in near future it is likely that even lower cost systems will emerge. This is one of the factors to improve the use of sensors in mining operations.

The current demands for applications of sensor in mining include requirements in hardware design and software tools. The hardware requirements include portability and ruggedized system. Robust systems are required for applications in harsh environment (e.g underground mine). The software requirements are related to advances in analytics from machine learning to improved statistical techniques thus to transform the multivariate raw sensor signals into knowledge about the materials under investigation. Attributed to various factors, direct fingerprinting of minerals or target elements using sensor signals might be challenging. However, the value of the property of interest can be inferred from spectral signals through indirect observations using chemometric techniques.

The other key requirement of sensors use in mining is sensor capability for remote applications. In this context, remote applications refer to few centimeters to meters distance between the material to be characterized and sensor (without actual contact). The recent advancement of hyperspectral cameras resulted in sensors that can be operated with field-based platforms (Schneider, S., 2011). This is useful for open pit mapping and the already existing field-based platform can be modified for underground applications (e.g application specific design for mine face mapping).
Imaging technologies provide information over wider area and give spatial context compared to point technologies (that measure spots). For example, georeferencing and mosaicking of the RGB images provided a comprehensive view of mineral distribution over the imaged part of the mine face. This is advantageous in understanding the spatial distribution and the relative abundance of minerals thus to infer grade indirectly. Coordinates of the sampled areas (channel centroids) were computed using the surveyed points and the point cloud generated using LIDAR. Therefore, spatially constrained chemical and mineralogical data were generated. This is useful to link the information from the different data sources based on location. However, the challenges related to sensors field of view, spatial resolution, positional accuracies and material variability should be taken into account.

4.3 Prospect for real-time analysis of material

Real-time material characterization requires rapid data acquisition, automated data processing and rapid return of results. Thus, it involves advanced platform that integrate hardware and a high performance computing software systems. Once integrated systems are developed, the predictive technologies can be deployed to deliver online data in different application areas. Such as face mapping, drill core logging and ore sorting applications. Material flow at the potential sensor installation sites along the mining value chain can be categorized into static and dynamic sites. Static sites are sites with relatively slow movement of materials such as mine face, drill core logging and muck pile applications. Whereas dynamic sites are those sites with a quick flow of materials. For example, the required real-time response of material characterization at the mine face might be in order of few hours to few days (after blasting was performed) and conveyor application could be in the order of milliseconds, and sometimes microseconds depending on the conveyor belt speed. Therefore, real-time material characterization at the potential sensor mounting sites along the mining value chain has different temporal aspects.

Predictive models were developed using the MWIR and LWIR reflectance spectra data, the models were used to discriminate the unknown spectra into ore and waste material types. The predictive models were trained for the prediction of elemental concentration, independent data sets were used to assess the predictive performance of the models. The acquired ore-waste classification accuracies and elemental prediction accuracies of the models indicate, the automation potential of the material characterization process. Going forward, a better prediction accuracy is expected with extended dataset in the calibration data. Likewise, for visually distinct minerals, mineral mapping using RGB imaging is a complementary approach to the conventional mapping. However, the former gives automated, reproducible and objective results. With well-calibrated prediction and classification models, automation of material characterization is achievable. Fast and better prediction results are possible with test case specific mineral libraries that take into account the spectral variation resulted from the heterogeneous nature of the deposit type.

4.4 Opportunities with fusing of data

In diverse areas of application, there has been an ever-increasing interest in a near complete description of materials using multi sensor data. One of such application areas is mining operation. A comprehensive view of materials in mining applications is advantageous; in understanding the process
of mineral formation, to understand the requirements in mineral processing, to find a relation with indirect proxies of minerals of economic interest, to provide mineralogical information for resource models and to convey safety information. Fusing of different data sources improves models classification and prediction accuracies, improves precision, improves availability and reduces uncertainty. Therefore, it significantly supports effective decision making in mining operations.

5 Conclusions

This contribution has demonstrated the usability of sensor technologies (RGB imaging, VNIR/SWIR hyperspectral imaging, MWIR and LWIR) for the characterization of a polymetallic sulphide ore deposit. The methodological approaches developed for each sensor technology resulted in usable results for identification, predictability and classification of the test case materials. The use of sensor combinations should aim to maximize the accuracy of (classification and prediction) models by minimizing the uncertainty related to models performance. Accordingly, the use of data fusion allowed for increased predictability and classification of materials.

The use of sensor technologies for raw material characterization is rapidly growing, and innovative advancements are observed. However, due to economically marginal deposits, deeper mine and complex geology, there is still a need to define and develop improved technologies and innovate approaches that can address the current and future mining challenges. One of the possible approaches is, to define and develop sensor combinations using scalable data fusion algorithms. Depending on the deposit type, the ultimate sensor combinations can be optimized and deposit specific mineral library can be developed using a combined sensor signal. Going forward, improved and automated material characterization is possible with integrated tools that combine sensor signals with material properties and ruggedized systems. Therefore, future research that address both the hardware and software requirements should be conducted to fulfil the gap between in-situ and online material characterization.

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Evaluation of Thermal Imaging based on LWIR cameras for Rock Characterisation

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ABSTRACT:

When talking about underground mining, most people think of a dusty, dark dirty and dangerous working environment. Indeed, miners often have to handle challenging environmental conditions. To make mining safer and more productive at the same time digitisation and automation of various mining processes are essential.

A key aspect for the digitalisation of mining processes such as the extraction or haulage is the data acquisition via suitable sensor applications. Within the Horizon 2020 funded project “Real-Time Mining”, the Institute for Advanced Mining Technologies (AMT) uses thermal imaging based on long-wavelength infrared (LWIR) cameras for rock characterisation purposes. Thermal imaging is a non-destructive and non-invasive method that records and visualises the emitted thermal radiation of objects. Via specific image processing algorithms, different rock types are to distinguish by their different thermal radiation. This may precipitate smart services such as material characterisation systems for geological surveying.

The use case for evaluating thermal imaging as technology for material characterisation is the underground test mine “Reiche Zeche” in Freiberg. In an iterative process, preliminary tests were carried out on rock samples under laboratory conditions followed by investigations directly at the mine face of the Freiberg test mine. This lead to standardised testing procedures and to further development of the robust camera housing and measuring equipment. Recorded data is consolidated in a thermal image database, which serves as a basis for the thermal image processing. Taking into account the particularities of thermal image processing, algorithms for pre-processing as well as textural and structural description of the sample images are designed and tested. Summing up, thermal imaging turned out to be a promising sensor technology for the acquisition and detection of rock structures and fractures in mining environments. Figuring out the feasibility of characterising the different rock types automatically, multiple characteristic values are selected and computed for samples of three defined rock classes.
Using machine-learning algorithms, an automated classification into defined rock classes could be realised. These scientific efforts may set the foundation for more continuous and selective haulage, transportation and extraction. At the same time, miners are kept away from dangerous workplaces.

1 A brief introduction to thermal imaging

To increase resource efficiency, productivity and safety of underground mining, various research and development projects deal with digitalisation and automation of the different processes within mining operations. One of them is the Real-Time-Mining project started in 2015. It’s aim “is to develop a real-time framework to decrease environmental impact and increase resource efficiency in the European raw material extraction industry” [1]. One fundamental part to reach this aim is the characterization of rock material by sensor technologies. The project partners consider various sensor technologies regarding material characterization at different steps of the mineral extraction.

Therefore, the Institute for Advanced Mining technologies (AMT) of the RWTH Aachen University validates thermal imaging as a method for material characterization of rock surfaces. For this purpose, measurements under laboratory conditions and in relevant environment in an underground demonstration mine are conducted. The aim is to first assess thermal imaging regarding it’s general usability to stand the harsh mining conditions. Based on this the feasibility to provide information about the mine face considering material, textural and structural changes by thermal image processing is to investigate. The measurements should also validate the overall differentiation of predefined rock types directly at the mining face, where the thermal camera is planned to be installed within the sensor concept.

1.1 Making the invisible, visible

In order to explain the technical qualities of thermal imaging in practical terms, the functional principle is explained in the following in comparison to the visual (RGB) cameras, which are often better known. RGB cameras are designed to capture images of reflected visual light, which contains information of what can be seen by the human eye. These images comprise the information of radiation in the electromagnetic spectrum in a wavelength of roughly 380 nm (Violet) to 780 nm (Red). This spectrum is also known as visible or VIS spectrum. Above the visible spectrum, in-between wavelength of 780 nm to 1 mm, the so-called infrared spectrum is located. Cameras which are designed to capture images of radiation out of this spectrum are summarized as infrared cameras. Cameras which operate in the long-wavelength infrared (LWIR) spectrum from 8 µm to 15 µm wavelength are often referred as thermal cameras, LWIR-cameras or rather thermal imaging systems. Thermal cameras are designed to visualize the so-called thermal radiation, which is emitted by each object with a temperature above 0 K. The commonly used uncooled microbolometer detectors consist of a matrix of semiconductor elements, each of which heats up depending on the incident radiation. This heating can be read out electronically as a voltage change. The voltage change of each pixel of the detector matrix will be output related to the calibration of the detector by the camera. In this way the received radiation is visualized in grey-scaled images, called thermal imag-
es. The higher the radiation intensity the brighter the according pixel in the thermal image. Figure 1 shows the principle of thermal imaging with its main measurement influences. [2]

![Diagram of thermal imaging](image)

**Figure 1: Measuring thermal radiation with a thermal camera (components are not to scale)**

The amount of radiation emitted by an object depends on the surface condition, temperature and material characteristics. In addition, the amount of radiation detected by the sensor depends on numerous extrinsic and intrinsic factors. This includes factors that maximize radiation intensity, such as reflections and interfering radiation. Furthermore, there are intensity-reducing factors such as the incomplete transmission of the atmosphere, entry lens and filter materials. If all these factors are considered properly during the acquisition of thermal radiation, thermal imaging represents a passive measurement technique which is independent of ambient light, non-destructive and, because of its wavelength, comparably insensitive to smaller particles like water and dust in the air (see Figure 1). [2, 3]
1.2 **Thermal cameras for material characterization in mining**

To assess the usability of thermal cameras as sensor technique for material characterisation in mining applications a SWOT (Strength, Weakness, Opportunity, Threat) analysis was performed. Table 1 contains the most relevant aspects that were used to compare thermal imaging cameras for mining applications with other imaging technologies such as RGB cameras and hyperspectral imaging.

Table 1: SWOT analysis for the use of thermal cameras in mining environment [4]

<table>
<thead>
<tr>
<th>Strength</th>
<th>Weakness</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Measurements are non-destructive and independent of ambient light</td>
<td>- Lower resolution</td>
</tr>
<tr>
<td>- Insensitive to smaller particles like dust and water in the air</td>
<td>- Export restriction due to dual-use</td>
</tr>
<tr>
<td>- Tested for underground mining</td>
<td>- Least commonly used for quantitative analysis</td>
</tr>
<tr>
<td>- Passive technology: No illumination required, natural thermal</td>
<td>- Camera need robust housing, protective glass (germanium or similar)</td>
</tr>
<tr>
<td>irradiation from every object (\rightarrow) geometrical and</td>
<td>has to be clean, housing has to be water- and dustproof</td>
</tr>
<tr>
<td>temperature information</td>
<td></td>
</tr>
<tr>
<td>- Works in wide temperature range</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Opportunity</th>
<th>Threat</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Technical solutions are emerging in terms of instrumentation and</td>
<td>- Implementation of systems is limited due to immature instrumentation</td>
</tr>
<tr>
<td>application</td>
<td>development</td>
</tr>
<tr>
<td>- Uncooled detectors are relatively cheap and small that they can be</td>
<td>- Cooled detector yields a better result than the uncooled one however</td>
</tr>
<tr>
<td>applied in field use</td>
<td>they are costly and consume more space (not particularly relevant for</td>
</tr>
<tr>
<td>- Most commonly used in other industries that it has a great potential</td>
<td>the application in mining industry)</td>
</tr>
<tr>
<td>for mining industry application</td>
<td></td>
</tr>
<tr>
<td>- Portable instruments are available</td>
<td>- For automation complex data processing might be needed</td>
</tr>
<tr>
<td>- Depending on specific application it can be used to differentiate</td>
<td></td>
</tr>
<tr>
<td>materials</td>
<td></td>
</tr>
</tbody>
</table>

Especially its independency to ambient light and additional illumination as well as its insensitivity to dust and moisture thermal imaging compensate challenges like export restriction and adapted housings. The SWOT analysis expresses that thermal imaging cameras are a sensor technique with much potential to observe mining processes. [5]

Due to the rapid development of thermal imaging within the last decades, the development of microsystems, infrared detectors as well as processing units evolved tremendously. For the following measurements AMT uses an uncooled camera core manufactured by the American supplier FLIR. The main advantages of this camera core are the comparatively small size with an optical resolution of 640 x 512 pixels at 7.5 mm focal length. In addition, the camera has a high thermal resolution with low power requirements. Finally yet importantly, the camera is characterized by its widespread use in industry, wide variety of variants and comparatively low price and the ability to capture images in raw format. As a protection against the rough conditions (e.g. splash-water, dust, etc.) in
underground mines an housing for the camera and its circuit board was designed and manufactured at AMT (see Figure 2). [6, 7]

The housing contains a window, which is made of germanium because it allows the transmission of LWIR radiation. Therefore, it is commonly used as material for lenses or for the protection of LWIR cameras. The housing keeps enough space to install power banks, which enable a mobile and flexible operation. The thermal camera is connectable to any portable computer via Ethernet cable. The image recording is realized using a software especially designed for the thermal camera system by AMT. [6, 7]

2 Measurements and preliminary tests

Because of the given advantages, thermal imaging is one of the sensor technologies, which is investigated in the Real-Time Mining project as a sensor for material characterization of rock surfaces. For this purpose, investigations on rock samples were conducted in laboratory followed by measurements directly at the face of the Freiberg’s Reiche Zeche test mine. The laboratory scale tests are conducted to investigate the general feasibility of rock characterisation via thermal imaging under defined conditions. In addition, the field tests are carried out to test the use of the sensor technology under relevant conditions. Those two use cases are completely different regarding their requirements and demands for the camera optics. For measurements directly at the face of the test mine a wide-angle lens camera (such as 7.5 mm focal length) seems to be appropriate. The advantages are that the taken image records a large area which leads to fast data acquisition times. A high field of depth facilitates relatively sharp imaging of the uneven rock surface. This is borne by the geometrical resolution. Considering the possibly uneven surfaces and the measurements directly at the mine face, a wide-angle lens camera was purchased under acceptance of the detriment it has for the optical resolution. [4, 8]
2.1 **Data acquisition in laboratory**

The laboratory tests are to conduct to investigate methods for rock characterization under defined conditions. During all performed field campaigns, rock samples were collected to perform the laboratory scale test work. This includes samples cut out of the orebody as well as fragments from the blasting activities of roughly 5 by 5 cm up to 15 by 20 cm collected at the demonstration block. The samples included the following rock types: ore, host rock and a type labelled as weathered rock by the project partners (see Figure 3). The different rock types look different enough, so that classification of the samples was performed manually. Qualified project partners from TUBAF randomly checked the executed classification. An additional confirmation of classification gave investigations with XRD of some samples, which were powdered and analysed during the project. [9]

![Figure 3: Images of different rock samples. From the left side: Ore/host rock; ore; host rock][9]

To perform the laboratory scale test measurements, AMT designed and manufactured a standardized test measurement setup shown in Figure 4. It excludes the influence of the surrounding radiation as good as possible. The iteratively developed test setup is made of wood with a horizontal extent of 60 cm x 60 cm and a height of 110 cm. The wooden lid is equipped with a hole inside. The thermal camera can be mounted with its field of view to the inside of the measurement setup on top of the box. Inside the box an adjustable wooden mdf plate is located to enable variable measuring distances for different sample sizes. With this measurement setup all laboratory scale test measurements were conducted. All the rock samples were labelled and the measuring conditions protocolled. The distance between camera and samples was determined between 16 cm and 6 cm, depending on the sample size. The surrounding temperature varied between 21 °C and 30 °C. In total around 200 rock samples were imaged. As not all of the samples consist of only one labelled class of rock, the according regions in the sample images were defined manually comparing to recorded RGB images. [9]
As mentioned above, the emitted radiation recorded by thermal cameras does not only depend on the material and on the temperature but also on the surface characteristics (e.g. metallic luster or LWIR-transmittance) of the measuring object. Therefore, single samples were cut in half in a workshop at RWTH. This lead to a flat surface and therewith a reduced influence due to irregular surface conditions. That allows proofing the hypothesis that different rock materials can be distinguished within a single thermal image. Figure 5 shows three thermal images of the cutted rock samples compared to RGB images of the same samples. It becomes clear, that some information such as the vertical and horizontal bands in the upper images or the mixture of “white” rock in the lower image are better recognisable in the thermal image. [9]
2.2 Data acquisition in field

To examine the usability of thermal cameras within underground mining processes and investigate the ability of rock characterization directly at a mining face, field test were to conduct. For the field test scenarios, measurements in the Freiberg Reiche Zeche test mine were to conduct multiple times. Thermal and RGB images of different parts of the ore reef and of the host rock were taken. After abandoning Freiberg Reiche Zeche mine in 1969 active mining in the mine was only for research purposes. Therefore, exposed reef and host rock surfaces have changed over time. During project this changed surface was called as weathered rock. The thermal images were acquired in the underground mine at a separately defined mine face, which was freshly blasted for two times within the project. For image acquisition, the thermal camera is mounted on a tripod and positioned perpendicular to the face as shown in Figure 7. Connected to the Toughbook via Ethernet, data transmission, recording and storage is realised. The ambient temperature in the underground mine is constantly between 10 °C and 13 °C with an air humidity around 97 %. This enables almost constant surrounding measuring conditions. [4]

The thermal images were acquired at the ~22m lateral extent mine face and at the demonstration block (DB) which has a lateral extent of ~3m. During the first field campaign, the mine face was imaged. The measurement distance between camera lens and face varied between 0.7 m and 1.40 m depending on the accessibility of the face. To cover the lateral and vertical extent of the mine face; two overlapping thermal images were taken at each reference point. During the second and the third field campaign thermal images were acquired after blasting at the DB. Therefore, images were acquired on the freshly exposed mine face which clearly shows ore and host rock materials. The defined DB contained the ore reef with an extent of up to ca. 70 cm surrounded by host rock. Classification of rock at the mine face in ore and host rock was done and supported by experts of TUBAF within the field campaign. [4, 9]

Figure 6 shows stitched images for the first three points of the first measuring campaign. On the upper part the figure shows thermal images in the lower part the relating RGB images. The depicted thermal images are filtered with a mean filter and adjusted in contrast for visualization purposes. The slightly different fields of view between thermal and RGB images base on the different opening angles of the camera lenses. The position to the face was the same for thermal and RGB imaging. [9]

During the first field campaign in July 2016 the face was heated up for a short period of time by halogenic lamps. The aim was to investigate which further information may be generated by activating the face. It became apparent that especially natural cracks and fractures as well as the surface geometry can be emphasized by the activating process due to increased temperature contrast and black body cavity effects in the image. In addition, the reflections of metallic surfaces are intensified and a phase transition is induced on moist rock surfaces. [4]

Figure 7 outlines the effect of heat activation to the underground rock surface. When comparing the non-activated to the activated thermal image it becomes apparent that activation by heat has an impact on thermal images of rocks. The activated thermal image seems to have a higher thermal contrast, bigger number of reflecting metallic rock partitions, improved differentiation between the host rock/ore border and overall better visibility of surface structures.
Figure 6: Stitched images for the points 1 – 3 of the first measuring campaign in July 2016. Thermal images (upper part), RGB images (lower part) [9]

Figure 7: RGB image of underground data acquisition (left), non-activated thermal image (top right), activated thermal image (bottom right)
3 Approach for material characterization for rock samples

Thermal images are the representation of the thermal radiation from an observation field in a greyscale. Thus, several digital image-processing techniques are applied to the thermal images to increase the degree of information. The different steps of image processing were developed using the images recorded under laboratory conditions and are mentioned in the following. They include a combination of established and non-standard image processing operations, which are especially developed at AMT. The image processing steps chosen for material characterization of thermal images mainly consists of:

- Pre-processing for noise reduction and detail enhancement
- Feature extraction for database creation
- Machine learning approach for rock distinction

Algorithms for pre-processing and segmenting the images are developed before feature extraction. With the aim of reducing irregular noise in the images during data acquisition all images are oversampled to compute an average image. This requires the camera not to move during data acquisition. Additionally, the images are corrected by regular interferences – caused by the radiation of the camera lens – with utilization of separate reference images. Furthermore, the images are tailored to their most important regions, also known as region of interest (ROI). Finally, the contrast of the images is spread over the entire image area in order to visualize differences in radiation in the best possible way. [9]

Subsequently, different characteristic values are computed of the pre-processed thermal images using MATLAB© for each rock sample. The characteristics are computed equally for each class of rock in order to compare the classes and find remarkable differences. More than 70 different characteristic values are researched and calculated to describe a rock type by virtue of the radiation intensities and their characteristic arrangement in the image. The number of characteristic values includes, among others, the characteristics of the Gray-Level Co-Occurrence Matrix: Contrast, correlation, energy, homogeneity and entropy with and without gradient determination as well as statistical and structural characteristics. All calculated values are collected in a database and sorted according to their prior defined rock class (ore, host rock, weathered rock). Figure 8 shows a scatter plot for some computed characteristic values for the three defined rock classes of the thermal images taken under laboratory conditions. [10, 11]

The results seem to be promising. Within the database even ore (blue) and weathered rock (yellow) seem distinguishable manually with the presented characteristic values. The results of other computed characteristic values are similar. [9]

Using the characteristic values a classification model was trained for the compiled database of the rock samples. The model bases on decision trees and was compared to other models using MATLAB© Classification Learner. For that, trainings and test datasets were defined. The results of the trained algorithm used for classifying the test data is figured in Figure 9. Thereby, the thermal images of the rock samples were segmented into regions of 32x32 pixels to increase data base which is crucial for machine learning approaches. [12]
Figure 8: Diagrams with different characteristic values for the different rock classes. Weathered rock, ore and host rock. Energy gradient and homogeneity gradient upper part, energy gradient and contrast gradient lower part [9].

Figure 9: Confusion matrix of rock type classification.
The results emphasize the promising results of Figure 8. Ore and weathered rock are predicted correctly with a rate of 77% respectively 87%. Merely host rock is predicted correctly with a rate of only 58%. Besides the above mentioned material characterization procedure for the differentiation of sample images captured in the laboratory, AMT currently focuses on the adoption of image processing techniques for field measurements. Summarized, the developed method proofed, that a rock characterization based on thermal imaging between different pre-trained rock classes is possible.

4 Conclusions and Outlook

Within the Real-Time-Mining project, thermal imaging was to investigate as a sensor technology for material characterization of rock surfaces. Therefore, the general usability of thermal imaging for mining was to be assess first. With a SWOT analysis, thermal imaging is compared regarding its strengths, weaknesses, opportunities and threats. Due to its unique properties and commercial availability, thermal imaging is identified to have a great potential for in-situ applications in underground mining. Systematic measurements on rock samples under standardized laboratory conditions as well as field tests in relevant environment in Freibergs Reiche Zeche mine were performed. Subsequently, the possibility of rock characterization by thermal image processing was to investigate. To this aim, the AMT developed the following procedure: Pre-processing with standardized and especially developed algorithms increased information content of thermal images. Thermal images of the laboratory rock samples were to classify manually and segmented automatically using adapted algorithms. Following, characteristic values were to research and compute with the aim of material characterization. Different classification models were to train and compare to each other. The generated results for differentiation between ore, host rock and weathered rock do already enable a rock characterization and should be investigated further to enable distinctions that are even more precise. A systematic evaluation of thermal activation methods and opportunities may increase the performance of the rock characterization. Additionally, a suitable way of visualization of classification results should be implemented. A detailed consideration of advantages and disadvantages of other sensor technologies may identify the best-practise combination for both use cases. In conclusion, it can be stated that the AMT has confirmed thermal cameras as suitable sensor technology for the mining industry and that the rock characterization by thermal imaging between predefined rock classes was successfully demonstrated. Integrating thermal cameras and thermal image processing in a real-time sensor framework could influence a mines sustainability due to waste reduction and optimized mineral processing.

REFERENCES


Moisture effect on hyperspectral analyses tested on bauxites and Ni-laterites samples

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ABSTRACT:

It is known that the moisture content has a strong effect on the data acquired by analytical sensors on drill cores. For example, the hyperspectral signal is attenuated and characteristic peaks disappear with increasing moisture contents. Therefore, substantial analytical deviations may occur in such data. The SOLSA project develops a combined expert system composed of sonic drilling providing coherent and complete Nickel laterite drill cores which will be analyzed directly by the SOLSA core scanner including an XRF, a profilometer, RGB, VNIR and SWIR cameras.

Drilling in Nickel laterite soils faces tropical climate conditions with up to 40 % humidity. Water originates from aquifers and meteoric water in particularly in the rainy seasons. Furthermore, even reduced due to sonic drilling, some water in the drill core will be related to the drill fluid.

We studied the moisture effect on bauxite and nickel laterite samples. The samples were immersed for 3 days in distilled water to be considered homogeneously and water saturated.

VNIR and SWIR hyperspectral data have been acquired on these samples at different levels of water content expressed as percentage of the mass of water on a moist sample basis.

Qualitative VNIR-SWIR spectra evaluation is based on the evolution of (1) diagnostic absorption features of major molecules including CO₃, Al-OH, Fe-OH and Mg-OH and (2) peak absorption of water and OH localized around 1400 nm and 1900 nm. These qualitative changes in the reflectance spectra were quantified using specific index such as (1) the kaolinite crystallinity Index parameter (KCI) or (2) NSMI index, a ratio between the re-
reflectance at a strong H2O absorption band (1802 nm) and the reflectance at weak water absorption band (2120 nm).

These preliminary results show that increasing water content of the target causes (1) the drop in acquired spectral intensities (2) the increase of water absorption features around 1400 nm and 1900 nm and (3) the loss of resolution of the characteristics CO3, Al-OH, Fe-OH and Mg-OH peak absorption. This loss of resolution is confirmed by the quantitative data calculated using the index parameters.

This will have a negative effect on automatic mineral proportion determination using unmixing techniques that rely on both reflectance intensities and diagnostic absorption features. However, it is worth noting that despite this loss of qualitative and quantitative resolution in the hyperspectral data, the characteristic absorption peaks on most of the samples, remain manually detectable, even for water content values higher than 30%.
SOLSA Drill, a modular and versatile tool for high quality sampling in heterogeneous soils

Harm Nolte, Peter Koert, Fons Eijkelkamp

Eijkelkamp SonicSampDrill

ABSTRACT:

The main features of the SOLSA Drill are:

- Highest safety standard for human and environment (latest EU Safety regulations, Tier 4 diesel engine)
- Modular approach (including optional automated rod handling module)
- Sonic drill head for highest quality and efficient sampling in heterogeneous soils
- Wire Line System for increased productivity at larger depths
- Core Handling System, including smart split-type liner for undisturbed samples
- Monitoring While Drilling system including Gateway for data acquisition and transfer of data to cloud

The SOLSA Drill is one of the three cornerstones of the H2020 EU Granted development of the SOLSA (Sonic On Line Sampling and Analyzing) Expert system

The new tooling system has been tested during an extensive testing campaign in France and further optimized as a result. The basic drill is assembled and commissioned and the modular automated rod handling system is now been fine-tuned in The Netherlands.

The final goal is the demonstration field test in the heterogeneous Laterite soils of the SLN Ni-mine in New Caledonia.
DriftLess: Underground Positioning using Bias Compensation for Inertial Sensors combined with UWB

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ABSTRACT:

This study considers the TNO DriftLess technology for the positioning of machines in the context of mining raw materials in underground mines. The positioning system is used to add position data to (material) measurement data. This way, the system enables smooth and efficient operations by tracking machinery inside a mine. This is more challenging than positioning above surface, due to the lack of a Global Navigation Satellite System (GNSS), such as the Global Positioning System (GPS). In this study ultra-wideband (UWB) is used to set up an infrastructure for range measurements. This system consists of a number of beacons at known locations. A position estimate can be established with more than three of these beacons in view.

However, ideally one would like to minimize the dependency to infrastructure, because the setting-up process of the beacons is time consuming. An Inertial Navigation System (INS) based on Inertial Measurement Units (IMUs) offers an infrastructure-free alternative using acceleration and rotational rate measurements.

To radically improve the dead reckoning position estimate of the INS, we propose the DriftLess Technology. DriftLess is a patented TNO technology where two IMUs are rotating on orthogonally placed disks, which allows estimating the time-varying bias of IMU measurements. An Unscented Kalman Filter (UKF) was developed for the combined DriftLess bias estimation and vehicle state estimation, including orientation, velocity and position. The position estimation performance was evaluated for the combined DriftLess technology, fused with either two or one range measurement from known locations, minimizing the dependency to the infrastructure.

Results show that a stable position estimate can be established, both with two and with a single range measurement from a UWB system. In both cases, the position errors are in the magnitude of one to two meters given continuous UWB signals.

In conclusion, a significantly decreased dependency to the infrastructure can be achieved by combining DriftLess technology with UWB. The accuracy is in the order of a few meters when a continuous UWB signal is present. Future studies could exploit this technology to
determine optimal beacon locations that minimize multipath interference and maximize field of view.

1 Introduction

Part of the challenge for mining operations is the localization of machines and material. A mine is excavated by a group of machines performing various tasks simultaneously at various locations in a mine. For both the task at machine level and group operation level a reliable position estimate is required. However, in contrary to above surface applications, GNSS systems cannot be used for position estimates.

A possible approach for underground positioning is the use of range measurements, for instance ultra-wideband (UWB). Range measurements depend on an infrastructure of beacons at known locations. Whenever more than three of these beacons are in view, a position estimate can be established.

A disadvantage of using range measurements is the time it takes to establish the infrastructure. For example, the corridor-structured mine environment needs elaborate analyses to enable a full position estimate at all times, due to bends in the paths. On the other hand, if many beacons are present around curved corridors, multi-path interference will arise from signals bouncing of walls, decreasing the reliability of the range measurement and thereby the quality of the position estimate. Therefore, a reduced dependency on the infrastructure is desired to simplify the operation.

A second approach is to use Inertial Measurement Units (IMUs) for underground positioning. IMUs provide acceleration and rotational rate measurements, that can be integrated over time to obtain a position estimate. However, offsets in the measurement will, due to the integration, result in the quadratic growth of errors over time. High performance IMUs with low bias are available in the form of Fiber Optic Gyros (FOG), these systems can cost up to tens of thousands of Euros. Low cost and miniature IMUs are available in the form of Micro Electro Mechanical Systems (MEMS), which find applications in smart phones. However the bias, and bias variation, of these MEMS IMUs is too large to be used for dead reckoning.

DriftLess, a patented TNO technology, boosts the performance of MEMS IMUs, making them usable for dead reckoning. This is achieved by estimating the time-varying biases, using IMUs that are rotating on orthogonally placed disks. This radically improves the dead reckoning position estimate of the IMU.

In this study the two approaches are combined. By using inertial measurements of the DriftLess system, a position can be estimated with only one or two beacons in view. This combined approach relaxes the requirements of the infrastructure, thereby simplifying the analysis of the mine environment and reducing multi-path interference.

A position estimate was computed from the combined measurements by applying an Unscented Kalman Filter (UKF). A UKF is an algorithm for data fusion, providing optimal estimates of the state given measurements and models of the system. In our case, the state contains the full vehicle state (orientation, velocity and position), and also the bias estimates. This way, the vehicle state
measurements contribute to more accurate bias estimations. The bias values are interpreted with a probability, allowing to estimate the bias variation as random walk.

To evaluate the extent to which a combined approach eliminates the infrastructure dependency, the resulting positioning estimates are analyzed in simulation and in an experimental environment, varying the amount of beacons in view (either zero, one or two). Besides this evaluation of the combined approach, the effect of the DriftLess bias estimation is studied in simulation and experiment.

This paper is structured as follows: Section 2 will elaborate on the working principles of DriftLess technology, the UWB system used and the UKF developed. Section 3 will present the results of a computer simulated DriftLess-UWB position estimation. Section 4 will show the results of different configurations in DriftLess with UWB on a single measurement run. Section 5 will discuss the possible system improvements.

2 Method

This section will describe the two used systems: DriftLess and UWB. Furthermore, the sensor fusion method will be elaborated upon.

2.1 DriftLess

An IMU is a sensor that typically contains a three axis accelerometer and a three axis gyroscope. By integrating these measurements an orientation and position estimate can be obtained. The IMU measurements have offsets referred to as biases. Unfortunately, these offsets are time-varying, due to uncompensated sensor dynamics. The measurement offsets cause linearly growing errors for the orientation estimate and quadratic growing errors for the position estimate. A common solution to deal with these errors is to apply a high pass filter eliminating the constant measurement offset. However, this high pass filter will ignore low accelerations and monotonous rotations.

DriftLess aims to provide a solution for estimating a time-varying bias in the gyroscope and accelerometer measurements. DriftLess was proposed by Marcel Ruizenaar et al. in 2013 (Ruizenaar, Hall, and Weiss 2013) and further developed in 2014 (Ruizenaar and Kemp 2014). The technology has been improved over the last years, by adding accelerometer bias estimation, enhancing calibration and applying the non-linear UKF instead of a linear KF. The concept behind this technology is to compare the difference in estimated bias in two orientations of the sensor for a measurement axis. This allows for bias estimation, assuming that the bias variation is negligible over a small time frame. To explain the equations, a simple one dimensional case will be elaborated upon, focusing only on the translational acceleration.

Assume we have two IMUs measuring the acceleration, obtaining the values $a_1$ and $a_2$, both for the same direction. The measured values can then be split into true acceleration $a_t$, the bias $a_{bias,i}$ and a noise component $v_i$, where $i \in \{1,2\}$ denotes the IMU. Subtracting the measurements of both IMUs from each other, the remaining signal will include the difference in bias and a noise signal, see equation.
\[ a_1 - a_2 = (a_t + a_{\text{bias},1} + v_1) - (a_t + a_{\text{bias},2} + v_2) \]
\[ = (a_{\text{bias},1} - a_{\text{bias},2}) + (v_1 - v_2) \]  

This on its own does not allow to make an estimate of the individual biases of the IMUs. Therefore, we perform a second measurement with both IMUs, whereby we change the orientation of the second IMU with 180 degrees. Denoting the second measurement with \( a_{i'} \) and the rotation matrix with \( R \) (for this one dimensional example \( R = [-1] \)), we obtain equation 2. Note that, besides a constant noise, we assumed that the bias remained constant, a reasonable assumption when the time between the two measurements is small.

\[ a_{i'} - Ra'_{2} = (a_{\text{bias},1} - Ra_{\text{bias},2}) + (v_1 - Rv_2) \]  

In the case of no noise and assuming a constant bias this would allow to solve for the biases by the following system, see equation 3.

\[
\begin{bmatrix}
1 & -1 \\
1 & -R
\end{bmatrix}
\begin{bmatrix}
a_{1\text{bias}} \\
a_{2\text{bias}}
\end{bmatrix}
= \begin{bmatrix}
a_1 - a_2 \\
a'_{1} - Ra'_{2}
\end{bmatrix}
\]  

In the case of noise, a dataset of measurements is needed to fit an optimal set of biases.

The principle introduced essentially proofs that a unique set of biases can be found if measurements can be obtained under two different, known orientations. Here we assume that the measurements in these two orientations are close to each other in time, making the bias variations negligible.

### 2.2 Hardware

Figure 1 shows the inside of the sensor box in which IMUs are placed on orthogonal mounted rotors. In Figure 1 the vertical and horizontal circular cavities are the locations of the rotors. Both rotors have two measuring positions. An 12 second out-of-phase step scheme rotates each rotor 180 degrees back and forward. This gives four combinations of rotor orientation that enables to estimate the biases on all three axis. On each rotor, the average of the measurements of four IMU chips were used during operation, to suppress sensor noise.

In order to use the acceleration measurements, a last correction is needed to obtain the translational acceleration values: we need to compensate for rotational acceleration. In this study we compute the translational acceleration at the center of the sensor box. However, since the IMUs are not located in this center, a rotational acceleration will result in perceived translational acceleration as well. This acceleration is compensated before averaging the measurements from the different IMUs. This wrongly attributed acceleration equals the cross product between the arm (from the center to the IMU) and the rotational acceleration, assuming that the sensor box and its components are rigid bodies. This rotational acceleration is estimated by differentiating the rotational rate measurements of the IMUs, over which a second order low pass filter is applied.
As stated before, the biases of the measurements have a time-varying behavior. Therefore, as time progresses the estimations of the biases should be updated. A Kalman Filter (KF) gives a suitable framework to make bias estimations recursively. A KF is a recursive maximum likelihood estimator that takes uncertainties of measurements and model predictions into account. It finds the most probable values of the state, $x_i$ given the measurement $z_i$. It predicts the next state using a state-transition model $A$ and an input model $B$ with input $u_i$, and the uncertainty of the model prediction $W$, also referred to as the process noise:

$$x_{i+1} = Ax_i + Bu_i + W$$ \hspace{1cm} 4

The observation model $H$ allows mapping the state on the measurement, where $V$ denotes the measurement noise:

$$z_i = Hx_{i+1} + V$$ \hspace{1cm} 5

The KF recursively estimates the state and its corresponding covariance matrix, using the equations 4 and 5. Please refer to (Ljung 1999) for the complete formulas.

### 2.3 Calibration of DriftLess

The principle of the DriftLess bias estimation relies on the assumption that the relative orientations between the IMUs are perfectly known. Therefore, calibration errors will directly be visible in the bias estimation. For example, if a measurement direction of an IMU is supposed to be perfectly horizontally, but has a slight calibration error, a part of the gravitational acceleration will be measured and wrongly attributed to the bias. A typical result of such a bias estimation is shown in Figure 2. Here we see a four step pattern in the bias as a result of the four possible combinations in orientations of the rotors.
To calibrate the system, accelerometer data was gathered while varying the orientation of the DriftLess sensor box and the rotation of the rotors. For each set of measurements, the DriftLess sensor box was standing still and thus measures only the gravitation. Differences in the sets of measurements can therefore be contributed to biases and calibration errors.

The calibration data was obtained by mounting the DriftLess sensor box on a Computer Numerical Control (CNC) milling machine, a machine capable of changing the orientation with an accuracy of up to 0.01. Measurements were obtained while varying subsequently the following variables:

1. The orientation under which the sensor box was mounted on the CNC machine. Measurements were taken under three orientations.
2. The rotation angle of the rotors that carry the IMUs. Since each rotor can be rotated by 0° or 180°, this resulted in four sets of measurements.
3. The rotation angle of the sensor box by the CNC machine. The CNC machine was programmed to switch between a rotation of 0° and 180°.

![Fig. 2: Estimated IMU accelerometer biases for uncalibrated sensor box.](image)

The next step is to find calibration matrices that fit the calibration data. For each possible calibration error a rotation matrix is defined which describes the rotation between the expected position and the actual position. This results in four calibration matrices: $C_{\text{mount}}$ treats mounting errors of the box on the CNC machine, $C_{\text{box} \rightarrow r}$ treats errors of rotor $r$ within the box, $C_{\alpha r}$ treats errors of rotation angle $\alpha$ of rotor $r$, and $C_{r \rightarrow \text{imu} i}$ treats errors of IMU $i$ on rotor $r$. These calibration matrices can be described as a single matrix using:
\[ C_{r_i}^\alpha = C_{\text{mount}} \ R_r \ C_{\text{box} \to r} \ R^\alpha \ C_{r \to \text{imu}_i} \]

Where \( R_r \) and \( R^\alpha \) are known rotation matrices, describing respectively the orientation of rotor \( r \) within the sensor box, and the rotation of the rotor under rotation angle \( \alpha \). In practice, we used \( C_{\text{box} \to r} = I \) because of the high accuracy of the milling.

Now the following equations hold:

\[
\begin{align*}
R \ C_{r_i}^0 \ (a_{r_i}^0 - b_{r_i}) &= g \\
\overline{R} \ C_{r_i}^0 \ (\overline{a}_{r_i}^0 - b_{r_i}) &= g \\
R \ C_{r_i}^{180} \ (a_{r_i}^{180} - b_{r_i} - \Delta b_{r_i}) &= g \\
\overline{R} \ C_{r_i}^{180} \ (\overline{a}_{r_i}^{180} - b_{r_i} - \Delta b_{r_i}) &= g
\end{align*}
\]

Where subscripts \( r_i \) denote IMU \( i \) on rotor \( r \), superscript \( \alpha \) denotes the rotation angle, \( a \) the acceleration, \( b \) the bias and \( \Delta b \) the bias difference between the sets of measurements. \( R \) and \( \overline{R} \) are the rotation matrices of the CNC machine, denoting respectively a 0° and a 180° rotation, while the gravitational vector \( g \) equals:

\[ g = [0, 0, 9.81]^T \]

A second set of equations further constrain the possible values for the calibration matrices:

\[
\begin{align*}
R \ C_{r_i}^0 \ b_{r_i} - R \ C_{r_i}^{180} \ b_{r_i} &= 0 \\
\overline{R} \ C_{r_i}^0 \ b_{r_i} - \overline{R} \ C_{r_i}^{180} \ b_{r_i} &= 0
\end{align*}
\]

![Accelerometer Bias](image.png)

Fig. 3: Estimated IMU accelerometer biases for calibrated sensor box.
Optimal values for the calibration matrices, given the data and equations 6 to 9 were found by processing the data in MATLAB (“MATLAB Optimization Toolbox” 2018) using the fmincon function. The calibration angles were optimized within constrained boundaries of $\pm 5^\circ$ and within $\pm 2 \text{ m/s}^2$ for the biases.

The final step for the acceleration biases is shown in Figure 3. After calibration, the step pattern has an amplitude of less than 0.005 m/s$^2$, corresponding to calibration errors in the magnitude of 0.02°.

2.4 Ultra-wideband

In this study an ultra-wideband (UWB) range measurement system is used to obtain range measurements. UWB is a radio technology that uses a wide frequency spectrum, enabling reliable communication with low energy over a short range. Typically, a UWB system for obtaining range measurements consists of a tag and a set of beacons. The beacons are placed at known locations, and the tag is attached to the moving object. The system works by sending a signal from the tag, which is received by the beacons, whereafter each beacon sends a signal back to the tag. By measuring the time between sending the signal and retrieving the answer, known as the Time of Flight, the tag obtains a range measurement. This procedure avoids the requirement to synchronize the clocks of the tag and the beacons.

Within this study the Decawave MDEK 1001 Development Kit has been used. This equipment has a location accuracy of less than ten centimeters, and a range up to sixty meters in line of sight conditions. Although the Decawave provides location information, we needed the raw range measurements for this study. These were obtained by adding an additional layer of software.

2.5 Unscented Kalman Filter

In this subsection the full Unscented Kalman Filter (UKF) will be explained. For the detailed UKF equations the reader is referred to (Merwe 2004). The UKF is a non-linear version of the original linear KF, where an unscented transform is used to estimate the distribution properties after a non-linear function evaluation (Julier, Uhlmann, and Durrant-Whyte 1995) (Julier and Uhlmann 2004).

As described earlier, the system consists of two rotors each providing an average IMU measurement. The full three dimensional state can be described as:

$$
\begin{align*}
\mathbf{s} &= [q_{(0,q_x,q_y,q_z)} \quad \mathbf{vel}_{(u,v,w)} \quad \mathbf{pos}_{(x,y,z)} \\
& a_{1,b_{(x,y,z)}} \quad a_{2,b_{(x,y,z)}} \quad g_{1,b_{(x,y,z)}} \quad g_{2,b_{(x,y,z)}}]
\end{align*}
$$

Where $q$ denotes the orientation using quaternions (Phillips, Hailey, and Gebert 2001), $\mathbf{vel}$ denotes the velocity in the body frame, $\mathbf{pos}$ denotes the position, $a_{1,b}$ and $a_{2,b}$ denote the accelerometer biases and $g_{1,b}$ and $g_{2,b}$ denote the gyroscope biases of the first and the second IMU respectively.

The kinematic equations are used to predict the state, see equations 10 to 14. Here $\mathbf{acc}$ and $\mathbf{gyr}$ describe the translational acceleration and rotational rate of the center of the box. When both rotors are in standstill the bias-corrected average measurement of the IMUs is used, when one of the rotors...
is moving only the IMU measurement on the non-moving rotor is used. The accelerometer and gyroscope are abbreviated with \( a \) and \( g \) respectively and used with subscript 1/2 for rotor number, \( m \) for measurement and \( b \) for biases.

\[
\dot{\mathbf{q}} = \begin{bmatrix}
-q_x & q_y & q_z \\
q_0 & -q_z & q_y \\
q_z & q_0 & -q_x \\
-q_y & q_x & q_0
\end{bmatrix} \mathbf{gyr}
\]

\[\dot{\mathbf{v}}e = \mathbf{acc} + \mathbf{gyr} \times \mathbf{vel} + R(q)^{-1} \mathbf{g}\]

\[
p\mathbf{o} = R(q)\mathbf{vel}
\]

\[
\frac{\delta}{\delta t} \begin{bmatrix}
\mathbf{a}_{1,b} \\
\mathbf{a}_{2,b} \\
\mathbf{g}_{1,b} \\
\mathbf{g}_{2,b}
\end{bmatrix} = 0
\]

Please note that \( R \) is the rotation matrix from body frame to inertial and that \( g \) is the gravitation vector. The state covariance is updated using the system noise, \( Q \), see equation 15. A rough estimation of the sensor noise effect is estimated by the first term and the second term is introduced to estimate bias variation. The variances of the IMU were deduced from standstill measurements.

\[
Q = B \begin{bmatrix}
\sigma_{\mathbf{acc}}^2 \\
\sigma_{\mathbf{gyr}}^2
\end{bmatrix} B^\dagger
\]

\[
+ \begin{bmatrix}
0 & \sigma_{\mathbf{acc}}^2 \\
\sigma_{\mathbf{gyr}}^2 & 0
\end{bmatrix} dt^2
\]

\[
B = \begin{bmatrix}
0_{4x3} & B_q & R(q) & 0_{3x3} \\
1 & R(q) & 0_{3x3} & 0_{12x3}
\end{bmatrix}
\]

To complete the UKF, there are three measurement equations besides the kinematic equations: the DriftLess update, the range measurements and a zero velocity update (ZUPT) measurement that can be triggered manually. The DriftLess measurement \( z_{DL} \) equations are related to the state as shown in equation 17. Where \( q_{r1} \) and \( q_{r2} \) are the quaternions describing the orientation of the rotors to the center of the sensor box.

\[
z_{DL} = \begin{bmatrix}
R(q_{r1})a_{1,m} - R(q_{r2})a_{2,m} \\
R(q_{r1})g_{1,m} - R(q_{r2})g_{2,m}
\end{bmatrix}
\]

\[
= \begin{bmatrix}
R(q_{r1})a_{1,b} - R(q_{r2})a_{2,b} \\
R(q_{r1})g_{1,b} - R(q_{r2})g_{2,b}
\end{bmatrix}
\]
The range measurements are related to the state by equation 18, where \((x_{b_k}, y_{b_k}, z_{b_k})\) describe the known location of beacon \(k\).

\[
    r_k = \sqrt{(x - x_{b_k})^2 + (y - y_{b_k})^2 + (z - z_{b_k})^2}
\]

The ZUPT measurement is given by equation 19. The measurement covariance matrix is deduced by analyzing the noise properties of the IMU and UWB in standstill conditions. Their variances were set over the diagonal and the off diagonal elements were set to zero, as there is no correlation between the errors of the two systems. The ZUPT variance was set to \(10^{-3}\).

\[
    [u \ v \ w] = [0 \ 0 \ 0]
\]

After the measurement update the quaternion is normalized to avoid drifting of numerical inaccuracies.

### 2.6 DriftLess IMU vs. Uncompensated IMU

To illustrate the added value of DriftLess, the quality of the position estimates were analyzed with and without the DriftLess bias updates. During these tests the DriftLess sensor box was used, which was standing still. In the first minute of each test, ZUPT was applied, to allow the UKF to estimate the orientation and bias. Hereafter, the ZUPT was removed and the position estimate had to rely on dead reckoning estimation.

![Position error graph](image)

**Fig. 4:** Position error of the sensor box without and with DriftLess update.

Figure 4 shows the time until a 50 cm position error was reached for both systems. It shows that the sensor box without DriftLess update reaches a 50 cm position error in 5.1 seconds, whereas the DriftLess update improves this to 15.7 seconds. This leads to a radically improved performance of
the complete system, in which the DriftLess solution is combined with UWB measurements, as will be described in section 4.

3 Simulation

A computer simulation was made for fusing DriftLess and range measurements to obtain insight into the performance of the position estimate.

A point mass was simulated, standing still for 60 seconds, after which it moves along a circular path with a radius of 15m. During the full simulated time a single range measurement was provided from a virtual beacon located at (0, −5, 0). All measurements were subjected to a noise signal with standard deviations of 0.05 m/s², 0.0005 rad/s, 0.05 cm for the accelerometers, gyroscopes and UWB respectively. Figure 5, shows the measurements over time, biases between [−0.8, 0.8] and [−0.0002, 0.0002] were applied to the accelerometers and gyroscopes respectively. Furthermore, an out-of-phase sinusoidal bias variation with period of 90 seconds was added.

![Fig. 5: The IMU measurements during the simulated movement together with the simulated biases and the estimated biases.](image)

Figure 6 and Figure 7 show the results with and without DriftLess update. The estimate with the DriftLess update is much closer to the actual position. It is clear that without the DriftLess update the UKF has trouble to maintain a smooth position estimate.
Two main reasons were identified for the improved performance of DriftLess. First of all, the system without DriftLess drifts quicker and has more difficulty finding the correct biases during the first 60 seconds. Secondly, it has no means to correctly interpret what part of the signal reflects the actual movement and what part is caused by time-varying bias. DriftLess clearly enhances the position estimate into a more accurate and smooth estimate. This result gives sufficient confidence in the added value of DriftLess to conduct an experiment.

![Fig. 6: The x, y plane simulated and estimated position with DriftLess update.](image)

![Fig. 7: The x, y plane simulated and estimated position without DriftLess update.](image)

4 Experiment

This section will describe the experiment set-up and the processed results.

4.1 Experiment Set-up

The experiment consisted of a trolley on rubber air inflated wheels, and UWB beacons at fixed locations. The test was conducted on a TNO parking lot. For the ground truth data a RTK GPS system was used which had cm precision. The RTK GPS was first used to measure the locations of the UWB beacons after which it was placed on the moving trolley.
The trolley had the DriftLess sensor box, RTK GPS, UWB tag, a computer and a car battery for power. All equipment was powered from the car battery so that the trolley was not hindered by any cable. The logging of raw data and processing of the UKF was performed on the computer. Figure 8 shows a picture of the placement of the systems on the trolley. Please note that the DriftLess sensor box, UWB tag and RTK GPS were positioned as close to each other as possible to avoid necessity for corrections in the algorithm. The raw IMU sensor data was logged at a 100 HZ update rate, the UWB and RTK GPS were both logged at 10 Hz update rate. The UKF was implemented in C++ and runs at 100Hz.

![Fig. 8: Experiment set-up on a rolling trolley.](image)

### 4.2 Experiment Results

The experiment was set up to show the effect of two independent variables: the use of DriftLess or no DriftLess update, and the number of used UWB beacons (the dependency to the infrastructure). The position estimation for both with DriftLess update and for 0, 1 and 2 UWB range measurements for a single experiment run are shown.

![Fig.9: Moments of UWB measurement of both beacons over time indicated with a colored vertical dash.](image)
Figure 9 shows the moments in time a UWB measurement was available from each of the two beacons by a colored vertical dash. Figure 10 shows the distance measurements of the beacons over time. Unfortunately, the UWB measurements were not continuous, during the test it was found difficult to maintain line of sight with both beacons over the complete run.

![Fig. 10: UWB distance measurement for both beacons over time.](image)

Figure 11, Figure 12 and Figure 13 show the position estimate results for 0, 1 and 2 UWB beacons respectively. Figure 14, Figure 15 and Figure 16 show the position error between the UKF estimation and the RTK GPS measurement. For the single UWB beacon case the beacon number one was used if available, if the beacon number one was unavailable the beacon number two was used. For the 2 UWB case both beacons were used if available. The measurement run starts with a standstill of 70 seconds. This was done to allow a 60 seconds ZUPT measurement in the UKF position estimation, as was also applied to the simulation. This allowed both the estimation with and without DriftLess to find an initial set of biases.

![Fig. 11: The true position of the RTK GPS, and position estimates with and without the DriftLess update, without using range measurements.](image)
Without UWB range measurements we see that the position estimate diverges out of the graph for both cases: with and without DriftLess update. However, the estimation with DriftLess update is clearly able to maintain the shape of the movement longer as all four corners can be identified, whereas the estimation without DriftLess diverges out of the graph after the first corner.

With a single UWB range measurements the position estimate drastically improves. Even for the case without DriftLess update, the first part of the trajectory is estimated reasonably well. However,
due to drift the position estimate diverges and starts to show large jumps. This confirms what was seen in the simulation results, where after some time the position estimate starts to make jumps as the solution diverges. Fortunately, this is not the case for the estimation with DriftLess update. Here the position estimate follows the trajectory for the full experiment run. The position error is in the order of 1-2 meters, except for the final seconds where it increases up to 5 meters. This increase in error at the end is expected to be caused by outliers in the measurements of the second UWB beacon, as the sudden jump in error corresponds to the moment where a measurement of this beacon is used.

Fig. 14: The absolute difference between the RTK GPS and the UKF estimation with and without the DriftLess update, without using range measurements.

Fig. 15: The absolute difference between the RTK GPS and the UKF estimation with and without the DriftLess update, using range measurements from one beacon.
When the DriftLess update was not used, the estimate with two UWB range measurements is longer capable to follow the trajectory compared to the case with a single UWB range measurement. Unfortunately, the position estimate still diverges after 45 seconds. This indicates that if no DriftLess update is used it is impossible to maintain a position estimate for longer periods of time. For the estimation with DriftLess update we see a more continuous position estimation compared to the estimation with one UWB beacon. The position errors are comparable to the single UWB beacon, where they stay within 2 meters for the run, except for the end where it increases to 4 meters. These errors are again expected to be caused by the second UWB beacon having outliers.

5 Discussion

This section will discuss the main performance consideration faced in this study for both the overall system and the TNO DriftLess technology.

5.1 System Improvements

A possible way to improve the performance could be to add additional information in the fusion process. A possibility within the current sensor suite could be to use the experienced vibration spectrum to automatically detect moments of standstill. A ZUPT measurement could be applied during the moments when a standstill is detected.

Another method could be to add different sensors to the fusion process. A valuable sort of information could be velocity information of any kind. For example, laser scanners could be applied that try to detect movements w.r.t. the static environment, or Doppler shift in the UWB measurement could be exploited to obtain a velocity component in one dimension.
5.2 DriftLess Improvements

The main challenge within the DriftLess concept was calibration. Calibration errors of a few tenths of a degree result in more than ten meters of drift in less than 30 seconds. This was solved by using a static calibration method. However, the physical mounting of the sensors can change over time, resulting in a degrading performance of the sensor box, which requires re-calibration. A possible way to solve this could be to let the UKF estimate changes in the calibration angles over time, however this could also reduce the computing speed of the algorithm.

The DriftLess sensor box currently has fixed measurement times when the rotors are in standstill. This causes DriftLess update to be discontinuous and can give some jumping behavior in the position estimate after longer periods of dead reckoning estimation. In theory the DriftLess update could be applied continuously, with a continuous rotation of the rotors, preventing jumps in the estimates. However, for this to work an accurate estimate of the rotation rate of the rotor is needed. Future research should see if this is possible.

Finally, the speed of bias variation that can be estimated depends on the time needed for the out-of-phase step scheme. The shorter the time needed for a full cycle of all steps, the quicker the bias variations that can be estimated. It was found in some standstill experiment runs that the orientation could drift with 0.2-0.3 degrees within a minute, but the DriftLess algorithm was unable to find bias variations decreasing this drift. This could indicate that this bias variation rate for the gyroscopes is too high to be estimated with the current step scheme.

6 Conclusion

This paper presented the advantages of using the DriftLess technology in combination with UWB range measurements to obtain a position estimate. The DriftLess technology improves the dead reckoning position estimate. If no DriftLess is used it was found to be insufficient to have two UWB beacons to maintain the position estimate for longer than 45 seconds. DriftLess allowed to maintain the position estimate even for a single UWB range measurement over the entire measurement run of over a minute. The position errors were 1-2 meters. This shows that DriftLess combined with UWB range measurements can be a sensor fusion solution that allows to decrease the dependency to infrastructure. Future studies could research the possibilities to exploit the sensor information by for example using automated ZUPT or by adding different sensors. The DriftLess concept has known weaknesses in its calibration, discontinuous updates and bias tracking speed. In future research solutions for these challenges will be explored.

REFERENCES


Multispectral imaging of minerals in flooded mines – a case study

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ABSTRACT:

A Multispectral Unit (MSU) was developed as part of the geoscientific instruments in the UNEXMIN project (www.unexmin.eu) which aims to develop a fully autonomous underwater vehicle (UX-1) to map flooded mines, operate to 500 m depth, and collect information about mineral resources.

As the UX-1 has to operate strictly in non-contact mode, to characterize the mineral composition, multispectral imaging was selected as a promising and feasible method.

The MSU was designed with a range of 400–850 nm, because the water severely limits the useful electromagnetic wavelengths of sensing. The selected range can work acceptably at 75 cm distance from the wall assuming sufficient water transparency. Due to physical-, energy-, time- and technological restrictions, the only possibility was to design our own multispectral unit with energy efficient monochromatic LEDs which can be controlled with millisecond accuracy and speed. A high resolution greyscale camera is used to record the intensity of the different wavelengths. The camera module is sequence synchronized with the triggering of different wavelength light sources. The spectra of individual points (pixels) on the wall are calculated during post-processing by the combination of the sequential images (14) and mapping them to real-world xyz-coordinates.

The colour of the water and its turbidity can have a strong effect on the measured mineral colour. To eliminate, reduce this effect a reference path was built into the MSU which is continuously measuring the water colour. To correct the wavelength specific absorption effect of the water the distance between the multispectral unit and each point of the wall is calculated.

The first calibrations of the MSU were at the University of Miskolc and the INESC-TEC at Porto where more than 60 different minerals – based on occurrence at test site mines – a white board – to calibrate the illuminated area – and a checkerboard – to calibrate the lens
distortion – were measured from 11 different distances with a stabilized robot and from 2 distances with a moving robot.

With the help of the laboratory measurements we were able to make the calibration of the system and the spectra of the minerals were created. More than 80% of the minerals are distinguishable with our method (pyrite, chalcopyrite, calcite, fluorite, etc.). During the tests where the robot was moving in front of the boards, we created a 3D point cloud with the navigational system and modelized the real environment of the measurements.

The first real mission of the Multispectral Unit was in Idrija, Slovenia, where the same mineral boards were measured inside a mercury mine. Several tests were made in the shaft with stabilized and moving robot and from different distances. Due to the dirty, reddish-orange water, only the closest images can be used for post processing. From ~ 30 cm distances we can identify the different spectra of the samples which are mostly the same than it was previously.

The first few sets of images were bright enough to extract spectra. However, the raw spectra for different minerals all appear very similar because of large differences in illumination obtained from the LEDs for different wavelengths. However, the aluminium frame holding the mineral samples allows these differences in brightness to be estimated from specular metallic reflections. This can be used to normalise the spectra, so that the minerals can be differentiated. In each case (sample minerals and metallic reflections) the reflection intensity was averaged over a square of 9 pixels.

Our MSU has huge possibilities in innovative commodity processing. As a future development this technology can be used even during offshore activities to sort gangue minerals from ore. With this method the amount of the waste materials – which would be lifted to the surface – can be radically decreased. The technology can also be utilized partially, e.g. the automatic spectrum fitting software could identify and select predetermined materials on a constantly moving conveyor belt. Additionally, the correction and spectrum building methods also can be used with other cameras (e.g. infrared, hyperspectral).

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UNEXMIN underwater 3D mapping with sonar and laser scan

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ABSTRACT:

This paper presents the real-time 3D mapping system designed for the underwater mine exploration UNEXMIN robot. The autonomous underwater vehicle was designed in the context of the European H2020 UNEXMIN project to explore flooded underground mines.

A vast number of abandoned mines exist in Europe with potential mining exploration interest. From these the available information is very diverse, ranging from complete unknown maps and mine state to well documented previous exploitations. Many of them have been abandoned for centuries and can potentially yield ore in economically concentrations.

The developed robot aims to explore these mines, providing not only detailed maps on their physical conditions but also to provide preliminary geo-physical and mineralogical information.

The robot (Figure 1) consists in a sphere of 60cm of diameter equipped with thrusters, a set of sonars, cameras, a variable buoyancy system, an internal pendulum for attitude control and a payload of instrumentation sensors for geo-physical characterization. The small size of the robot is dictated by the intending operation environment and many mine galleries are very narrow and difficult to traverse. These dimensions together with the spherical shape (to minimize possible trappings and entanglements with obstacles) pose harsh limitations to the possible set of sensors to equip the robot.

For environment characterization (Figure 2,3) the perception system it should not only provide detailed 3D modelling but also coherent and as much as possible complete imaging coverage, and also integrate mineralogical information gathered by the instrumentation sensors.

The presented work addresses the sensor choice and structure of the real time 3D mapping system. It presents the perception software and computational architecture with de-
tails on its distributed features. The mapping sensors are composed by one multi-beam imaging sonar, 5 digital cameras and a set of custom developed laser based structured light systems.

The mapping system will be described and the global sensor extrinsic parameter calibration will also be addressed. Test tank results will allow to characterize the 3D mapping system and are presented some results in the Kaatiala (Finland) field trials and the Idrija mine tests (Slovenia) to demonstrate it in operational environment.
Unlocking Online Sensor Potential: Innovative Approaches for Real-Time Resource Model Updating

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ABSTRACT:

A key requirement for the mining industry is to characterize the spatial distribution of geometry and geometallurgical properties of the ore and waste in a mineral deposit. Due to geological uncertainty, resource models are crude representations of reality and of limited value in forecasting. Information collected during the mining production process is therefore highly valued in the mining production chain. New sensor technologies allow the characterization of the extracted ore during different phases of the mining production process, typically during grade control. The spatial location, the quantity of the material observed and the mining dilution will vary in each of the grade control phases. A major challenge is the potentially non-linear relation between sensor observations and the modelled attributes of the deposit. Models for mine planning are usually based on exploration information from an initial phase of the mineral extraction process. The integration of sensor data measured at different support along the production line into the resource or grade control model allows for continuous updating and has the ability to provide locally more accurate estimates.

This contribution presents results of an industrial scale demonstration of grade control model updating, which has been performed as part of the H2020 project Real-Time Mining. The focus is on aspects of the practical implementation in an underground environment. Algorithmic details are presented, data management aspects highlighted and results shown and interpreted.

Acknowledgements

The Real-Time Mining project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 641989.
1 Introduction

In mineral resource extraction, a main objective is to meet production targets in terms of ore tonnage, mineral content and grades. This contributes to the optimization of mill throughput and metal recovery while minimizing costs. Generally, short-term production scheduling and operations control require a decision making process that should maximize the value of the mining operation by considering the maximum amount of information available at the time. Most of the decisions are based on models of the spatial distribution of attributes of interest within the ore body. Typically, grade control models predict attributes relevant to processing and recovery operation at the scale of a selective mining unit (SMU). The available information consists of exploration holes augmented by chip or channel samples from the grade control process. This data base is not only spatially sparse, but also has a time delay, as samples are typically analysed online in a laboratory. It can take several days before results are available; the SMU may already have been mined with decisions about its destination/processing made on an outdated model. This is especially problematic in highly complex deposits.

In many operations, online sensors provide a large amount of geo-referenced data during production monitoring. The ability to incorporate these data rapidly into grade control models offers the opportunity to continuously improve the grade control and resource models while mining the deposit. To incorporate production data obtained during the mining process in real-time, recent studies have developed a method for backward integration of online production information to improve the accuracy in grade control models, (Benndorf, 2015). The integration applied a methodology akin to an ensemble Kalman Filter methods were implemented for bulk mining operations in open pit mining settings (Wambeke and Benndorf, 2016; Yuksel et al., 2017) and showed improvements in prediction accuracy. The potential of these methods is obvious, since they are capable of assimilating direct and indirect information improving the resolution at a local model scale.

Besides algorithmic details, a main success factor of implementing real-time updating of resource and grade control models is the ability to manage a very heterogeneous spatio-temporal data base and information flow. To guarantee an efficient updating workflow, different spatially and timely constrained data sets and models need to be integrated in a consistent way.

The focus of this contribution is on the operational implementation of the ensemble sequential model algorithm in underground mining settings considering thin ore veins. Here, a generalized mining process is considered consisting of a cycle that involves drilling, blasting, loading, scaling and supporting. Different initial models constrained to diverse information have been simulated in order to test the updating algorithm in different scenarios. The contribution first reviews the theoretical background. Second, implementation details including the data and information flow and the geo-data management are presented. Finally, results from a full-scale industrial case study at the Reiche Zeche Mine in Freiberg are shown and interpreted.

2 A Brief Review of the Updating Approach

The integration of data observed during the mine production process is achieved by using an inverse modelling approach. The inverse problem aims to determine the unknown model (system) parameters by making use of the observed (state) data. In the present case, the models which shall be up-
dated, are generated by geostatistical techniques. The model parameters are ore attributes at each location \( x \), which are described by a regionalized random variable \( Z(x) \). A set of random variables at different locations is summarized in a random field \( Z(x) \), which, under the assumption of a normal distribution, is fully described by its first two order moments, which are the mean vector and the spatial covariance.

The idea behind the proposed updating procedure is to solve the inverse problem related to following equation:

\[
z(x) = A^{-1}(d)
\]

where the term \( A^{-1}(d) \) is the inverse of the forward model. This maps the attributes \( z(x) \) from a spatial support onto the observations \( d \) on a timely support. The operator \( A \) links the spatially modelled attributes \( z(x) \) with the observations \( d \) and provides a forward model. This model can be non-linear, mainly due to the change of support and possible non-linear relations between modelled block values and observation. This non-linearity and computational efficiency is the main reason, why ensemble sequential updating methods are preferred for updating grade control models. In (Wambeke and Benndorf, 2017) a first attempt is documented to translate the concepts of sequential updating from systems and control theory to mineral resource extraction. The introduced concept is based on the Kalman Filter approach with an observational matrix \( A_t \). The sequential updating procedure is expressed by the updated state estimate:

\[
z(x)_t = z(x)_{t-1} + W_t(d_t - A_t z(x)_{t-1})
\]

where the difference between the model-based predictions \( (A_t(z(x)_{t-1}) \) and the observations \( (d_t) \) gives the innovator term of the equation. \( z(x)_t \) is a vector of the spatial attribute after \( t \) updates. This is a vector state variable of dimension \( N \), where \( N \) is the number of mining clocks considered. The matrix of weights \( W_t \) is of size \( M \times M \) and balances out the accuracy of new observations obtained with the prior information. This weighting factor is expressed as:

\[
W_t = C_{t-1,zz}A_t^T(A_t C_{t-1,zz}A_t^T + R)^{-1}
\]

where the term \( C_{t-1,zz} \) is the covariance matrix of \( M \times N \) size and the \( A_t \) of size \( N \times M \) is the observation operator, which expresses the change of support of the observations as a a non-linear operator. The term \( R \) is the error matrix associated with the device accuracy.

The analytical computation of the prior error covariance \( (C_{t-1,zz}) \) and its propagation through the process may by expensive in computational terms. Therefore, the second part of the equation is implemented as Ensemble-Kalman Filter (see Wambeke and Benndorf, 2017) to estimate the forecast error covariance \( C_{t-1,zd} \) and the observation error covariance \( C_{t-1,dd} \) empirically. This is more flexible and efficient in computational terms.

The algorithm presented here is able to assimilate online sensor data provided during the mining production process to the grade control model. The algorithm can deal with different aspect, such as the simultaneous integration of information from different localizations. The forward simulator model reflects the support of the observational error that is present on the support of the information. In general, the approach can be used for multiple correlated attributes.
For more details on the algorithm, the interested reader is referred to published literature (e.g. Prior et al, 2019).

3 Algorithmic Implementation Details for Underground Mining Settings

Extraction Process

In this section, the information that can be obtained in each operational phase is described. Just as the extraction process, this information has to be based on an operational planning in underground mining settings. This operational planning is related to the decision-making process and model requirements for optimal control.

The first step of the extraction process is in the pre-blasting phase, when the SMU to be extracted is exposed and has to be characterized. The composition of the mineral assemblage, geochemistry and the vein thickness within the mine-face can be obtained based on different imaging technologies from the exposed face. Typically this information is pixel based and can be considered as point-wise information. Therefore, there is no change of support since the exact location of the pixels/data points is known and the observation support matches the support of the resource model considered. This is considered as highly precise location of thickness of the orebody. This procedure corresponds to the Figure 1 - part A.

Using the updating approach, the information is fed back in real-time into the grade control model before blasting in order to better estimate ore/waste ration and the mineral composition within the SMU's. The second step in the extraction process chain consists of blasting the SMU that has been selected for extraction. Ore is drilled, blasted, loaded and transported. The transport may be by means of a conveyor belt and leads to a primary crusher and subsequently into a storage bin. During this phase the material can be characterized by sensors installed along the conveyor belt. The grade/mineral content is measured and represents a mean value of the whole SMU extracted. The grade and mineral content prediction of extracted SMU is usually performed as the mean value of grid nodes within the SMU in the grade control model. This corresponds to Figure 1 - Part B and C.

When mining thin veins, the material scanned includes dilution from waste rock. The diluted grade and mineral content results from the ore/waste ratio within the blasted SMU and the grade or mineral content within the vein.

Figure 1 shows the considered SMU extraction process in the mining area. Figure A is mine face characterization, where (1) is the sensor that characterizes the mine face (2). In addition, channel samples (3) may be obtained out of the mine face during grade control. The SMU that will be blasted is (4) and the whole drift to extract is (5). Figure B shows the process after blasting represented by the muck pile (6). Figure C shows how the loader that brings the material to the conveyor belt (9) and these are analysed by sensors (8). Figure D shows the sensors characterizing the volume of material extracted (10). The grade control model is updated after obtaining the information in the sub Figure A, C and D.
Methodological Details for Underground Mining Settings

The mineral deposit extracted at the Reiche Zeche is characterized by different attributes. In the present work these are arsenic, zinc and lead grades and thickness of the vein over each grid. As in any geostatistical approach, attributes are modelled by the univariate spatial random function previously described, $Z(x)$. This variable may refer to different supports over the whole mineral extraction process. Figure 2 represents a flow-chart of the data assimilation process for grade control model updating. This is divided in two main supports. The grid support is a fine scale support that matches with the initial obtained data support as chip samples, channel sampling, boreholes or sensor measurements over the mine face. The resource model is simulated at grid support. The SMU is the operational support, which is the basis of decision-making. The block model is obtained by re-blocking of grid nodes of the resource model $Z(x_n)$ into a new $B(x_m)$. The grid model has a number of $n$ cell grids and the block model has a number of $m$ SMU.

As discussed in (Benndorf, 2015; Wikle and Berliner, 2007), the sequential updating methodology is optimal when all variables involved are Gaussian. For most variables it is necessary to perform a mapping to a Gaussian space prior to updating. The most common transformations is based on quantile matching as Gaussian anamorphosis (also known as Normal Score Transformation) (Simon and Bertino, 2009; Carrassi et al., 2018).
### Data Assimilation for Grade Control Model Updating

<table>
<thead>
<tr>
<th>Grid Support</th>
<th>SMU Support</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Observations</strong></td>
<td><strong>Modelling</strong></td>
</tr>
<tr>
<td>Exploration data $Z_0(x_0)$</td>
<td>Prior Grid Model $Z_0(x_0)$</td>
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<tr>
<td></td>
<td>$\Phi_n^{-1}$</td>
</tr>
<tr>
<td>Gaussian data $U_0(x_0)$</td>
<td>Prior Grid Model $U_0(x_n)$</td>
</tr>
<tr>
<td></td>
<td>$\Phi_m^{-1}$</td>
</tr>
</tbody>
</table>

**Mine Face Mapping**

- $A_{t+\frac{1}{2}}(Z(x_n))$
- $d_{t+\frac{1}{2}}(x_n)$
- $\Phi_m^{-1}$
- $\Phi_m^{-1}+$ Reblocking
- Updated SMU Model $B_{t+1}(x_m)$
- SMU-Grid
- Data Assimilation Algorithm
- Non-Updated Grid Model $Z_{t+1}(x_n)$
- SMU Observation $d_{t+1}(x_n)$
- $\Phi_m$
- Updated Grid Model $U_{t+1}(x_n)$
- $\Phi_m^{-1}+$ Reblocking
- Updated SMU Model $B_{t+1}(x_m)$
- Grid-Grid

**Bulk Sampling**

- $A_{t+\frac{1}{2}}(Z_{t+\frac{1}{2}}(x_n))$
- Data Assimilation Algorithm
- Non-Updated Grid Model $Z_{t+1}(x_n)$
- SMU Observation $d_{t+1}(x_n)$
- $\Phi_m$
- Updated Grid Model $U_{t+1}(x_n)$
- $\Phi_m^{-1}+$ Reblocking
- Updated SMU Model $B_{t+1}(x_m)$
- Grid-Grid

---

**Fig. 2:** Data Assimilation Work Flow for the Reiche Zeche case study.

Two different anamorphosis transformations ($\Phi$) have to be considered the different supports:

$$U_0(x_0) = \Phi_n(Z_0(x_0))$$  \hspace{1cm} (4)

$$Q(x_m) = \Phi_m(B(x_m) + E(x_m)) \quad \forall \ x_m \in S_m$$  \hspace{1cm} (5)
Equation 4 shows the anamorphosis transformation for the grid support ($\Phi_n$). This can be obtained from the initial information time 0 at the locations $x_0$. After applying this transformation, a simulation of the random field on a grid support has been implemented by sequential Gaussian simulation. Equation 5 shows the anamorphosis transformation for a SMU support ($\Phi_m$). This can be obtained after adding a random noise $E(x_m)$ to each block of each realization of the re-blocked model $B(x_m)$. This error is associated to the bulk sampling measurement and it has been simulated assuming a mean value equal to zero and uncorrelated covariance $C_{vb}$. After transforming the initial information, the simulation of the two attributes is performed by sequential Gaussian simulation.

Figure 2 states two different sources of observations: those made by mine face mapping and those made by bulk sampling. Mine face mapping obtains grid support observations while bulk sampling obtains SMU support observations. The mining process considered here makes it characterized by a two step monitoring/update approach of the SMU’s. A time step $t + 1/2$ an updating is performed based on mine face mapping and at time step $t + 1$ the update is based on bulk information from the muck pile. Both measurements map the same SMU, but each considers a different support. Thus, one full block updating step consists of two measurements and two updates. The reason of this double updating over one SMU is to update the information about the thickness and the grade before blasting as input for blast-block delineation. Later information of the muck pile is assimilated for logistics planning and production control.

With the proposed methodology, there exits two different data assimilation windows depending on the observations that are being obtained. The window grid-grid that update based on grid observations and the windows SMU-grid that update based on SMU observations. Nevertheless, both windows update the grid model.

One of the main difference between each assimilation window is the forward operator that maps the observations to each model.

$$A_{t+\frac{1}{2}}^{+1^{(k)}}(\{Z_t^{(k)}(x_n) \mid x_n \in S_t\}) = \{Z_t^{(k)}(x_n) \mid x_n \in S_{t+\frac{1}{2}}\} = Z_{t+\frac{1}{2}}^{(k)}(x_k)$$ (6)

$$A_{t+1^{(k)}}^{+1^{(k)}}(\{Z_t^{(k)}(x_n) \mid x_n \in S_t\}) = k^{-1} \sum_{x_n \in S_{t+1}} Z_t(x_n) = B_{t+1}^{(k)}(x_k)$$ (7)

Equation 6 is the forward operator that maps the mine face observations into the resource model. There exists a direct correspondence between observations $x_k$ and grid nodes $x_n$ since both represent the same support. Equation 7 is the forward operator that maps the SMU support observations into the resource model. This operator selects the grid nodes contained in the SMU observed and estimates its average value from the forward model.

After applying the forward operator and mapping the predicted observations into the forward model, these are transformed to the Gaussian space by the defined anamorphosis transformations.

$$Y_{t+\frac{1}{2}}^{(b)}(x_b) = \Phi_m(B_{t+\frac{1}{2}}^{(k)}(x_b)) \quad \forall \quad Y_{t+\frac{1}{2}}^{(b)}(x_b) \in \mathbb{R}^{b \times I}$$ (8)

$$U_{t+1}(x_k) = \Phi_n(Z_{t+1}(x_k)) \quad \forall \quad U_{t+1}(x_k) \in \mathbb{R}^{k \times I}$$ (9)

The next step is the actual updating and the back transformation. Details are skipped here as these are already documented in (Prior et al, 2019).
**Sensor Data**

Two different types of sensors are considered, sensors characterizing the exposed mine face and sensors installed in the conveyor belt that characterize the blasted material. The sensors that characterize the mine face provide georeferenced information within the area that is being characterized and allow an accurate estimation of the vein thickness and thus the volume of ore to be extracted.

Previous work has been conducted (e.g. Desta and Buxton, 2017) in the application of sensor technologies for raw material characterization in underground mining settings within the Real-Time Mining project.

After blasting, the material that is being characterized on the conveyor belt cannot be georeferenced to a higher resolution than a SMU support. Thus, fuzziness in material tracking due to muck pile management and loading is assumed for the sensor data on the conveyor belt. To accommodate this fact, different errors have been associated to the different sensors accounting for the accuracy of the measurements. Note that for the testing, the blasting of the SMU is assumed to be performed perfect (as planned). Information about over-or under breakage will be considered during operation using 3D laser profiling data from the actual blasted SMU block. These profiling sensors provide information on the surface of the SMU before and after blasting. With this information, the volume of SMU extracted is estimated (Figure 3).

![Fig. 3: Comparison of laser scan point clouds between two epochs for volumetric calculation.](image)

In order to incorporate sensor measurements from diluted ore into the prediction model, an approach has been implemented that considers different mineral and vein thickness related information in the grade control model. After blasting, the material is carried on conveyor belts where sensors are able to measure diluted grade. Equation 9 provides the calculated value for recovery model. This combines the final percent dilution related to the resource model and the mining reserve estimated related to the grade control model.

\[
\text{Diluted Grade} = \frac{V_O \times O\%}{V_O + V_B}
\]  

(10)
V_B (Volume of the SMU as blasted) can be obtained from Laser profiling of the mining SMU. V_O is the volume of the vein contained in the extracted SMU. In case of perfect blasting this volume equals the area of the SMU multiplied by the mean thickness value. This information is available from the already updated model based on the face image. Thus, the diluted grade sensed on the conveyor belt provides indirect information about the SMU grade.

4 Geo – Data Management

For real-time updating of grade control or resource models, a large amount of data has to be integrated in a consistent manner. For the Reiche Zeche case study, data have been acquired during a four years period of the Real-Time Mining (RTM) project. Data formats range from simple one-dimensional representations up to three-dimensional data and models with more complicated derivations (see Figure 4).

![Different types of acquired data at the Reiche Zeche Mine](image)

For scientific case studies, all these data typically are stored in a simple file hierarchy, loosely coupled through file and entity names. As the data evolves from usual measurements to more derived products, the file structure becomes even more complicated and an efficient data handling becomes nearly impossible. At this point, modern spatial database systems are suitable tools to efficiently store and organize data. With these tools, it is possible to store the data itself and the relations between these data.

A database system (DBS) consists of a database management system (DBMS) and one or more databases (DB). The database management system is the software to manage and manipulate the stored data and the database itself is the body to structure and store all related information. Usual relational database management systems (RDBMS) store data in tables and realizing relationships between several entities (simply spoken: one line in such a table) by connecting tables. For handling
spatial data, modern RDBMS include extensions to store detailed information for a spatial object, e.g. the coordinate system. Additionally, the query language is extended to manipulate this kind of data efficiently. It is possible, to perform coordinate transformations or even to derive new geometrical objects based on already stored ones.

By simply storing a timestamp as an additional attribute for an entity, a spatial database can be extended to a so called spatio-temporal database. In contrast to the spatial extensions of the query language, the handling of this additional dimension (the time) is still not well advanced and not well supported by a standardized query language extension.

Database modelling is the procedure to develop a database scheme for the available unstructured data. This database scheme consists of all the rules according to which the data is stored. In addition, it defines the relationships between the data. This step is the essential modelling step. The database scheme defines not only the possibilities of storing the data and relationships, it also allows or restricts the possibilities to query the data.

There are several RDBMS available, which offer a spatial extension. The most advanced are the commercial Oracle database with Oracle Spatial and the open source PostgreSQL with PostGIS. Both systems are OGC (Open Geospatial Consortium) compliant. For this case study, PostgreSQL/PostGIS has been chosen as it offers all needed features at no costs.

Considering all available data, the following database scheme has been developed for the case study. Besides the self-explanatory parts, special design decisions are described in detail.
Fig. 6: Data base scheme for Resource model updating at the Reiche Zeche Mine
The main data follows a simple relation:

| Measurement Value „at“ Location |

According to this relation, the two main tables are “geometry_data” and “geometry_property”. “Geometry_data” holds all the simple geometries like points, lines and polygons. “geometry_property” holds all the property values – the measurements. These two tables are connected by a so called n-to-m relation which means that it is possible to connect more than one entity in table “geometry_data” to more than one entity of table “geometry_property”. This construction is needed to gain more flexibility. For example, the channel samples could be viewed as point-based data or as area-based data.

For a proper use of all the functionality a spatial database system can offer, PostgreSQL/PostGIS needs to know the coordinate system of the stored geometry data. With the EPSG-code exist a common definition of almost all coordinate systems in the world. Unfortunately, the coordinate system of the test site “Reiche Zeche” is a compound coordinate system, which does not exist as a single EPSG-code. X and Y are projected Gauß-Krüger coordinates (EPSG 3398) and the Z component is a gravity-related height (EPSG 5785). Therefore, an own coordinate system was needed to be defined for use with PostgreSQL/PostGIS. The OGC defines the so called Well-Known-Text (WKT) to describe geometry data in a human readable way. By using WKT, a compound coordinate system for RTM can be constructed (see Figure 7). The final coordinate system definition was defined with the “free” EPSG-Code 989898 within the PostgreSQL/PostGIS database realization.

```
COMPOUNDCRS["RD/83 / Gauss-Kruger zone 4 + SNN76",
    PROJCS["RD/83 / Gauss-Kruger zone 4",
        GEOGCS["RD/83",
            DATUM["Rauenberg_Datum_83",
                SPHEROID["Bessel 1841",6377397.155,299.1528128, AUTHORITY["EPSG","7004"]],
                AUTHORITY["EPSG","6745"]],
            PRIMEM["Greenwich",0,AUTHORITY["EPSG","8901"]],
            UNIT["degree",0.01745329251994328, AUTHORITY["EPSG","9122"]],
            AUTHORITY["EPSG","4745"]],
        UNIT["metre",1,AUTHORITY["EPSG","9001"]],
        PROJECTION["Transverse_Mercator"],
        PARAMETER["latitude_of_origin",0],
        PARAMETER["central_meridian",12],
        PARAMETER["scale_factor",1],
        PARAMETER["false_easting",4500000],
        PARAMETER["false_northing",0],
        AUTHORITY["EPSG","3398"],
        AXIS["Y",EAST],
        AXIS["X",NORTH]
    ],
    VERTCRS["SNN76",
        VERT_DATUM["SNN76",2005,AUTHORITY["EPSG","5183"]],
        UNIT["m",1.0],
        AXIS["Gravity-related height",UP],
        AUTHORITY["EPSG","5785"]]
]}
```

Fig. 7: WKT coordinate system definition for the RTM database. Given Code 989898.
The stored measurement values also need special handling. Besides exact values exist relative values with a value qualifier describing the actual value is below (<) or above (>) a certain value/threshold. This is realized with a separate linked table “value_qualifier”. This table defines the different types of qualifiers which are referenced in the “geometry_property” table. This results in a measurement definition of “value” from table “geometry_property” plus the referenced “value_qualifier”.

Another “value” extension and special design decision was made to model results of the analysis of drill core samples. To utilize the “linear coordinate system”-feature of PostGIS the bore holes are geometrically modelled as one line with only the starting and the ending point. These points are defined with an additional “measurement” value. In this design this value describes the depth of the bore hole – the distance from the starting point along the line. Therefore, the start point gets a 0.0 and the end point gets the actual length of the drill core (table: geometry_data”). The drill core samples itself are described with the measurement value (table: “geometry_property”) only valid within a specific interval (table: “value_interval”) along the line/drift core. PostGIS can utilize this interval values as “measurement” values to calculate coordinates along the referenced line/drift core (table: “geometry_data”) at query time. Therefore, storing each drill core sample’s geometry is not needed – it can be derived at query time using spatial functions of PostGIS.

Besides these main tables there exist various auxiliary tables to store meta data and original data. For example, in “property_blob” are all original files saved which were the source for the individual properties.

In conclusion, this scheme describes the storage and querying of most of the available data to date. The realized link between measurement value and underlying geometry makes it possible to efficiently handle and query the geodata of the Real-Time mining project.

5 Results of the Reiche Zeche Case Study

Setting and Data

The demonstration of the updating algorithm has been performed in conjunction with the demonstration of sensors for material characterization, production visualization and control and optimization within the Real-Time Mining project during 2016 to 2018. This use case refers to a particular production panel the Wilhelm Stehender Nord orebody of the Reiche Zeche mine in Freiberg. The orebody belongs to the second level of the mine (around 150 meters depth). The elevation of the area is around 282.6 meters asl (above sea level). The vein has a dip of around 50 degree E-W with a thickness from 0 to 1.4 meters (Figure 8).
Initial Resource and Grade Control Model

The genesis of the orebody and associated zonation requires a separate modelling of vein geometry and spatial distribution of grades within the vein. Modelling the vein has been performed in the following steps:

- Variogram modelling of the vein footwall and thickness based on measurements from face mapping along the panel
- Application of geostatistical conditional simulation to create realizations or ensemble members of surfaces representing the hanging and footwall of the vein.
- Joining surfaces to create realizations of the solid representing the vein.

For the Freiberg case study, the main minerals of interest have been defined. These are arsenopyrite, galena, pyrite and sphalerite. The remaining minerals are of no techno-economic significance and have been clustered as waste. Based on the spatial continuity derived from 114 channel samples taken from an analogue neighbor block, an initial unconditional grade distribution has been modeled using the Turing Bands method. With this, 100 realizations of the vein geometry and spatial distribution of grades of interest (As, Zn and Pb) have been generated on a dense grid. The grid spacing has been chosen as 0.2 x 0.2 x 0.1m, this model is referred to as resource model. Grid nodes have been relocked according to the mine plan. The SMU size considered is 1m by 1m x 2m. Each block is presented by 100 realizations of the attributes:

- Ore/waste ratio (derived from block and ore volume),
- Mineral contents of main minerals and
- Grade of zinc and arsenic as representative elements for this case study.

Figure 9 summarizes the work flow.
Fig. 9: Workflow of creating the initial resource and grade control model.

**Results**

During the experimental investigation of the Real-Time Mining project in the Reiche Zeche mine, several data acquisition campaigns have been conducted. These data sets are partially based on new sensor developments, such as LIBS, and partially based on laboratory analysis for benchmarking purposes. Geometric information have been achieved using terrestrial laser scanning (TSL). These data refer to different stages in the extraction process and are labeled

- Epoch 1: before blasting, only prior information
- Epoch 2: blast block characterization using drill core samples (online core logging)
- Epoch 3: Channel samples are taken at the mine face and vein geometry is derived from TSL

These 3 epochs refer to one blasting cycle. During the Real-Time Mining projects, four blocks have been considered (see Figure 13). For the illustration of results, data from block 1 (Epoch 1 to Epoch 3) are used for assimilation. The effects on the blasted block, but also on the three blocks that are mined next, are investigated.
From a geochemical point of view, the information about the mining block under consideration prior sampling and after sampling is shown in histograms in Figure 11 and 12 exemplarily for zinc. The histogram in Figure 11 shows the information available before sampling the blasting block. Since no grade control data at block scale have been available at this stage, this frequency distribution represents a global assumption on possible grades in the block derived from previous exploration of the panel.

Figure 12 shows the histogram of grade control data from bore holes and face sampling. This represents the local distribution of grades. Obviously, these local data derived by online sampling deviate from the first global guess and show on average higher grades. This can be seen as an expression of the additional information obtained during grade control sampling.
Using above described methods developed within the Real-Time Mining project, grade control data have been assimilated in the grade control model based upon their availability in time. For evaluating results, four mining blocks have been considered:

- Block 1: the next blast block that has been characterized by grade control
- Block 2: the subsequent block along the mining pass (one block-length away from Block 1)
- Block 3: the subsequent block along the mining pass (two block-lengths away from Block 1)
- Block 4: the subsequent block along the mining pass (three block-lengths away from Block 1).

Figure 13 shows an overview of the location of Block 1 to 4 within the mining panel.

Due to spatial correlation, the information obtained for Block 1 are expected to also affect Block 2 to 4. Due to the increasing distance, this effect will be decreasing towards Block 4. Figure 14 shows the results. For each of the blocks the estimated probability distribution of Zinc grades for each of the epochs considered. From left to right there is an increasing information content, first by assimilating bore hole data and second by assimilating grade control data.
Fig. 14: Development of Zinc grades with each update for the four blocks that have to be mined next.
**Interpretation**

Considering Block 1, there is a significant change of the grade probability distribution as a result of updating. The new information gained through bore hole information (Epoch 2) cause already a strong shift of the expected block mean grade towards higher values. Also, the uncertainty of prediction decreases, which is indicated by the smaller Inter Quartile Range. After assimilating, face sample values, which provide the highest amount of block-related information, the mean grade shifts slightly towards lower values compared to epoch 2. The uncertainty further decreases significantly. These observations are not surprising, since additional dense information taken directly at the block is used to update the block grades. The new aspect is that this update can be done in nearly real-time, as soon as sensor data become available.

![Fig. 15: Statistical indicators for the zinc grade in Block 1 before and after updating.](image)

Considering Blocks 2 to 4, similar effects can be observed. With increasing distance (from Block 2 to Block 4) the impact of the new data becomes less. Still, Block 2 experiences significant improvement in prediction and Block 4 shows also some recognizable improvements.

![Fig. 16: Uncertainty development for zinc prediction within Block 1 to Block 4.](image)
Table 1 summarizes results for the attribute Zinc.

Tab 1: Statistical indicators for zinc in Blocks 1 on to 4 before and after updating.

<table>
<thead>
<tr>
<th>Block 1</th>
<th>Zinc in %</th>
<th>Prior</th>
<th>Update 1 (Bore hole)</th>
<th>Update 2 (Face mapping)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min.</td>
<td>0.5</td>
<td>3.1</td>
<td>2.8</td>
<td></td>
</tr>
<tr>
<td>1st</td>
<td>1.4</td>
<td>3.9</td>
<td>3.2</td>
<td></td>
</tr>
<tr>
<td>Median</td>
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<td>3.3</td>
<td></td>
</tr>
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<td>Mean</td>
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<tr>
<td>Max</td>
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<td>5.2</td>
<td>3.9</td>
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<table>
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<tr>
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<th>Zinc in %</th>
<th>Prior</th>
<th>Update 1 (Bore hole)</th>
<th>Update 2 (Face mapping)</th>
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<tbody>
<tr>
<td>Min.</td>
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<td>Mean</td>
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<td>Max</td>
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<th>Update 2 (Face mapping)</th>
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<tbody>
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</tr>
</tbody>
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With these results it can be concluded that for the case of this particular mining panel and considering Zn, assimilating online grade control monitoring data into grade control models offers a huge potential in predicting block grades. Due to its timely advantage compared to offline analysis and offline modelling, this new approach offers better predictions very fast. These can be directly incorporated into production logistics or short-term scheduling for the next shift or day.
In the appendix, similar to Figure 14, improvements for Block 1 to 4 are illustrated for the elements As and Pb.

6 Conclusions

This contribution summarizes methods, experiences and results of a full-scale implementation of grade control model updating in a highly selective underground mining setting. The benefit of a fast integration of online grade monitoring data becomes obvious. The predictability of grade, tonnage and mineral content significantly improves for a short-term planning range, covering in this case the four next blast blocks. The method appears to deliver robust results. In subsequent work, the method will be expanded to the multi-variate or compositional case. A key requirement for a successful implementation and routine application is a well thought-through data management system that enables fast access and availability to most recent data and models. As these data originate typically from different groups, a consistent data treatment is essential. This particularly applies the use of a consistent geodetic coordinate system for geo-referencing data and models and a time synchronization. Only, if these essentials are met, the updating will deliver qualitative good results and eventually improve operational performance.

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Appendix: Development of As and Pb grades with each update for the four blocks that have to be mined next.
Virtual Reality Mine Planning and Operation Control

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ABSTRACT:

3D-based visualizations and even Virtual/Augmented Reality applications are used in a variety of areas. For example, in special applications for architecture or the automotive industry, but also in web-based mass solutions for end users, such as in virtual room or kitchen planners. Due to today's availability of very powerful hardware, such applications can also be used by end users directly on a smartphone or tablet. However, in the mining industry, mostly very simple and schematic 3D visualizations have been used for several years. Here, the 3D model primarily serves as a navigation aid through the large data sets.

XGraphic GmbH has been developing individual software and technical systems with interactive graphical components for a wide range of applications for nearly 25 years now. The focus is on software applications for infrastructure and information management, planning tools, process monitoring and applications for mobile devices. As a rule, the presentation of data is always based on a suitable 3D model. Therefore, we are currently working on the development of a multifunctional and flexible software framework based on our many years of experience in this field. The tool provides interfaces and components for modular visualization solutions for use in raw material industry and to implemented customer-specific applications. On top of that, virtual and augmented reality technologies could be integrated in order to offer further added value.

The visualization cockpit developed in the context of the Real-Time Mining project is an interactive 3D application with different screens for the clear representation of the data resulting from the sensor-based monitoring processes as well as the calculated potentials for process optimization based on the 3D mine geometry.

The modules include the visualization of the deposit-model, 3D extraction planning, integrated data of the positioning-system as well as the visualization of sensor and machine performance data. Different tools will have been developed for supporting operation control and optimized decision making based on real-time data from the centralized database.

The visualization cockpit is divided into two levels: The planning views offers various screens in which the information relevant for short-term planning and process optimization is displayed. In the operation views, current positions of mobile units and various sensor data are displayed georeferenced on the 3D model.
The main screen of the cockpit is based on an interactive 3D representation of the mine layout. The user can rotate, move and zoom in/out the model to create individual views. Based on this representation, all active operating points are displayed with the corresponding basic information on mineral content, tonnage and information on the mining plan. By selecting an operating point, a detailed view of the working face can be displayed with graphical information on the relevant deposits, the so-called Face View. This shows the local Grade Control Model (short-term model with block contents and properties of the ore) for optimizing the drilling schemes and enables access to current data from material recognition (photos, classifications, ...).

The implementation is carried out based on the latest technologies with respect to special software development requirements such as user-friendliness, performance, compatibility, modularity and expandability. Within the scope of development, the expertise of the partners involved in the implementation of graphical applications and process monitoring systems for use in underground mining will be drawn upon. Beyond that, new hardware technologies offer a variety of possibilities for innovative extensions of the visualization cockpit. The use of virtual reality hardware enables immersive exploration of the 3D data. In this way, the relevant decision-making processes can be made even more intuitive.

The realization of Virtual Reality applications is nowadays already possible with commercially available computer hardware. All you need are suitable screens, a powerful graphics card and shutter glasses. In addition to VR display on screens, visualization via VR headsets is another possibility. Such a headset is put on by a user and offers an even more immersive experience than conventional VR applications due to its isolation from the environment. A VR headset consists of an integrated solution for displaying a 3D image adapted to the respective eye and tracking the position and alignment of the VR headset.

New hardware technologies offer a variety of possibilities for innovative implementation of visualization solutions. The use of virtual reality glasses enables immersive exploration of the 3D data. This is even more intuitive and convenient than a “classic” 3D visualization and offer great opportunities to support optimized decision making.
Use of time series event classification to control ball mill performance in the comminution circuit – a conceptual framework

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ABSTRACT:

Metallurgical attributes are often omitted from the mine to metal valuation models since they are either absent or unreliable. However, recent developments in sensor technology indicate the potential to collect information on metallurgical properties directly or by measurement of proxies. Integrating this information back into the resource model would provide the necessary means to move towards a more comprehensive and reliable evaluation model. To obtain truly optimized mining decisions it is necessary to consider the metallurgical attributes since they are indicated as root cause of changing plant performance. Therefore, a better metallurgical characterization of the plant feed over time is required, which allows for a more optimal selection of process control settings. Different material types have varying effects on machine performance in the comminution circuit. This makes it possible to refer a performance change as a response to different geological attributes. Hence, the corresponding geological machine behaviour can be controlled by defining effects of behavioural geology. This paper introduces a framework containing data fusion of sensor responses which resemble geological attributes and subsequent multivariate time series machine behaviour characterization for improved process control in the comminution circuit. The conceptual framework’s approach is that process control in future will be supervised by profound knowledge from sensor data indicating geological behaviour. The use of multivariate time series deep learning is proposed to create innovative process control. This innovative control is then a response to a combination of advanced sensor data (XRF, LIBS, FTIR, etc.) with more traditional sensor data (throughput, density, etc.). These advanced sensors provide more knowledge about material specific properties in the form of discoverable events. This new knowledge is important in the vision of behavioural geology, to better understand the influence of geological behaviour on machine performance.
1 Introduction

A reason that machine performance optimisation in the comminution circuit is so important for mining companies, is that the crushing and grinding units are among the most energy-demanding machines (Jeswiet & Szekeres, 2016). A key aspect for optimisation is modelling of the metallurgical behaviour of the plant feed on, for instance, the ball mill performance. This might be challenging due to the lack of knowledge on how different types of materials react to different operational settings (Suriadi, et al., 2018). Therefore, to obtain optimized mining decisions it is necessary to consider metallurgical attributes which affect the comminution circuit. Optimisation can improve the recovery and reduces the energy utilization as well as the chemical usage per ton of processed material (lower the environmental footprint). Consequently, overall operation expenditures will drop making lower grade ore economic while increasing the mineral resources that are available for conversion to ore reserves. Traditional geometallurgy requires a lot of metallurgical laboratory testing of secondary rock attributes (e.g. strength, hardness), what results in a low number of data points and from which plant performance is modelled and designed. The metallurgical test data are generally not indicative of the root cause affecting plant performance (e.g. presence/absence of certain material types).

This root cause in geometallurgical variation is clearly found in the chemical composition, mineralogy, texture and fracturing of plant feed. These primary rock attributes define the secondary material attributes, are spatially abundant and can be cheaply measured in very large quantities from available sensor technology (e.g. hyperspectral, FTIR, XRF, LIBS, Raman, etc.). Use of this data provides the means to link geometallurgical variation with machine behaviour due to geological changes. Therefore, if geological behaviour due to variation is understood then machine performance can also be understood and controlled.

An attempt to find the effect of geological attributes from feed material on the machine performance by a machine learning process is shown in (Tessier, et al., 2007). They used a machine vision approach for on-line estimation of rock mixture composition and linked this to grindability. Although this methodology allows for the recognition of the type of rock, no further effort was done to implement the conceptual workings in practice. That means that there is still no understanding by the resource model from the process, and thus a ball mill does not know what type of material it gets as feed. Therefore, development of an implementable system for machine performance control is critical to take the next step in an optimized comminution circuit.

Nowadays, abundant real-time sensor data are collected which is available for use. Initial work by Benndorf, et al., (2014) and Wambeke, et al., (2017) already indicated the importance of combining high density time series data. Their work indicated that correlated measured variables should be jointly considered to update the resource models (Benndorf, et al., 2014) and geometallurgical models (Wambeke, et al., 2018). Neglecting these correlations will result in a loss of information. The geological attributes of plant feed data are key for the ball mill performance, so if it is possible to have data fusion of various sensors responses that could resemble all the material, then it could give insight in the ball mill behaviour. Note that machine behaviour determines the machine performance and is therefore in this paper used interchangeably in the context of the ball mill.

The largely unexplored machine learning techniques area of mineral processing, geological and mineralogical data and time series data is interesting to consider in future research (McCoy &
A recent study had focus on the analysis of impact of secondary rock properties and operational settings on key performance indicators of interest. They used regression and classification techniques to separate the influence of rock characteristics from operational settings on plant’s performance, and found operating parameters that affected the plant performance, independent of material properties (Suriadi, et al., 2018). Contrary to this, the proposed framework described later, does not separate geometallurgy and operational settings to find the similar relations with ball mill performance for instance. This will be done with a deep neural network which explores the source of changing ball mill behaviour, the geological attributes. Eventually, it finds the interrelation of sensor data, and combines this in a behaviour label. This is possible, because specific domain knowledge about the geological attributes is obtained by sensors. Using the classified label results, it is possible to adapt the process control settings for the incoming material.

This paper introduces an innovative conceptual framework which aims that process control for the comminution circuit in future will be supervised by profound knowledge from sensor data measuring mainly primary geological attributes of plant feed. The expected success of this framework is due to the gained knowledge in the field of domain specific sensor data. This helps to design and develop an integrated and data-driven framework to control machine performance in the comminution circuit. It consists of an approach where sensor data is combined and consequently resembles the geological attributes of the feed. This input is classified by a deep neural network, which determines the optimum control settings in the comminution plant. First, the layout of the conceptual framework is described. Then, the concept and recent developments are elaborated within the three major pillars of the framework. Thereafter, design challenges are discussed. The concept presented here is part of an ongoing research work.

2 Towards geological behaviour based process control

Figure 1 illustrates the geological behaviour based process control framework, wherein future process control settings can be predicted and adjusted based on the defined effects of behavioural geology. This is achieved by the following seven steps:

1. Sensor data from measurements of metallurgical primary and secondary attributes from a feed batch are collected based on timestamps from the appropriate data. Combing the right data from the right moment relies on work done by material tracking. In this stage this work is in progress, but further excluded from the framework.
2. These data are combined and resemble the incoming plant feed for a selected time frame. This data combination contains the data from geological attributes of the feed.
3. A trained deep neural network (DNN) model uses the results of step 2 as input to characterize the corresponding machine performance behaviour. Attached with this label are model-based predictions for the control settings of the machine.
4. Due to the obtained knowledge on geological plant behaviour, process control settings can be suggested and adjusted.
5. The feed material is processed and the actual plant performance is recorded.
6. Comparison of the model-based predicted performance (step 3) and actual measured performance (step 5) can result in two outcomes. The predicted behaviour corresponds with the actual behaviour; assume that the geological attribute classification was correct. The actual
behaviour differs from the predicted behaviour; assume a misclassification. These test data should be stored for future model updating.

7. At regular intervals, the DNN prediction model should be retrained. The new training samples should initially consist of correct and misclassified samples. In later stages mainly misclassified samples from step 6 should be considered.

The success of implementing this geological behaviour based process control framework lies in the foundation of the three main pillars which characterize the work:

1. Sensor based material characterization; from raw sensor data to fused data and input for a deep neural network.
2. Multivariate time series analysis applied on sensor combinations; create a link between geological attributes and machine performance label.
3. Material behaviour based process control; the effects on process settings.

The following sections provide an overview of recent developments in these three pillars, and describe the new concepts and proposed way of implementation.

3 Raw sensor data fusion

Geological attributes are identified as source of changing plant behaviour. Therefore, they can act as key characteristics to resemble material. The occurring differences can be found for example in lithology, mineralogy, texture, fracturing, degree of alteration, degree of ore mineralization. These profound differences can be found due to recent developments in sensor technology which have
shown the potential to collect information on metallurgical properties directly or by measurement of proxies.

Recently, the use of RGB imaging and FTIR sensors were combined in mapping an underground mine wall section (Desta & Buxton, 2017). The following conceptual framework that they developed, indicated that the use of sensor combinations for a raw material characterization in mining is still very limited. Automation of the material identification process by combing sensors signals is not defined at all. The proposed framework was focused on data fusion at three different levels for classification and prediction of mineral properties (Desta & Buxton, 2018). To resemble material, a hierarchical high-level data fusion method of different sensors is proposed, where no specific interpretation of the data (related to material characterization) is required. Since the characteristic attributes of minerals are encapsulated in the fused response, it is expected that fused data can characterize the typical plant behaviour. The rational for data fusion is because of importance of the effect of the material attributes on machine behaviour. When understanding is necessary, it can be found by the underlaying characteristics found in the fused data and can tell more about categorical variables, such as ore types or lithologies. No statement is made that understanding the fused data is not important, it is more seen as a validating tool of the data that is worked with. Therefore, material characterization in this framework is based on the formation of multivariate time series, which are derived from fusion of sensor response data, what results in a quantitative treatment.

Selecting the type of sensor data to characterize material depends on discoverable events in the sensor response data. Several sensor technologies that have the potential to indicate visible events include Raman and Laser-induced breakdown spectroscopy (LIBS), Visible Near Infrared (VNIR) and Short Wave Infrared (SWIR) hyperspectral imagery for determining textures and mineralogy, Mid-Wave Infrared (MWIR) and Long-Wave Infrared (LWIR) for assessing silica content and X-Ray Fluorescence (XRF) for geochemistry.

The main work in this pillar results in a training dataset for the deep neural network. The approach to achieve this is shown in Figure 2, and indicates how it represents multivariate time series data and event labels. a) Displays sensor measurements of plant feed at different locations. By means of material tracking the time-moments of similar material measurements can be linked (not part of this framework, but ongoing research). b) Indicates data fusion from specific sensor responses and how that results in multivariate time series data, that provides the input for the DNN and used to extract features. c) Plant feed is processed by the ball mill and the corresponding performance is obtained in the form of time series data. Changes in the performance behaviour can be indicated as events which, therefore resemble the response of the performance behaviour of the ball mill due to changing geological attributes. Domain knowledge can give insight into the cause of plant behaviour changes, but is expected to not be necessary for indicating behaviour changes. The event labels are combined with the input time series data to form a training dataset, which will be used as input for the deep neural network.
Multivariate time series analysis for behaviour prediction

The sensor responses from the plant feed contain the relevant information to identify the root cause of measured differences in plant behaviour. Therefore, the combined sensor responses resemble the plant feed at $t$, a specific moment in time and changes per sensor update. Geological behaviour is now resembled by multiple univariate time series, $\mathbf{x} = \{x_1, \ldots, x_D\}$, where $x_i$ is a measurement of time series $\mathbf{x}$ at timestamp $i$, and $L$ is the total number of timestamps for this time series (Wang, et al., 2016). Each new sensor update will provide a new set of data points in time.

A specific sequence in one of the responses of the multivariate time series data could indicate a changing ball mill performance and can be labelled as an event which characterizes the ball mill behaviour. Therefore, these responses are subject to time series event classification. The approach is that from the multivariate time series data (Fig. 2b) and corresponding event labels (during training, obtained after processing), a classifier is trained which can map from the space of possible inputs a probability distribution over the event label set. Following, the highest probability will determine the label type $y_i$, that corresponds to a certain type of (predicted) ball mill behaviour. If no clear quantitative relationship between material sensor data and equipment performance can be found, then this label approach should be more generalized. This resorts to a more qualitative approach and, for instance, focusses on low, medium or high performance classes.

To accomplish this goal, this paper proposes the use of machine learning techniques to suggest and train predicted relationships between fused data as input variables and predicted ball mill performance as output. It is suggested to use a deep learning framework for multivariate time series classification to create a deep neural network (DNN) model. The trained model is then able to delineate
the root cause of performance change. The choice and design of this neural network is subject to the problem of machine behaviour control and to our best understanding no such operational mining related problem is currently solved by a deep learning framework. Therefore, no existing train and test data sets exists and no definite design choice is made yet. Note that this model might be material type dependent. The development in this pillar mainly consists of building the framework around a data set \( D = \{(X_1, y_1), (X_2, y_2), ..., (X_N, y_N)\} \), where \( X_i \) are the fused data time series (set of \( x \)), \( y_i \) is the predicted ball mill performance event-label from the event set \( Y \), and \( N \) is the data set size. A DNN-based model is excellent in finding the relationship (features) between the time series and labels. It can design the representable features from the raw data automatically by self-learning hierarchical feature representations. A bigger test dataset ensures higher classification accuracy.

A model is created and trained with the training set to learn feature representations. Within the DNN architecture for time series data, possibly a Convolutional Neural Network (CNN) which generally composes of two parts is suitable. The first part consists of alternating convolution and pooling layers, which generate and learn features from raw data automatically. A simple mechanism explanation is that, after the weight initialization of the model, a forward pass through the model is applied to the first convolutional layer. There the time series is passed through different filters which each is designed (unique weights) to extract a characteristic behaviour of the time series. The second part, uses the learned features from the previous part to either train a fully connected multi-layer perceptron (MLP) for classification purpose (Zheng, et al., 2016) or directly classify it by pooling (Zhao, et al., 2017) and softmax operations (Wang, et al., 2017). After the model is trained it can be tested and validated with a test data set. For the working of CNN models the interested reader is referred to (LeCun, et al., 2015).

Time series have dynamic properties, because new time series data \( X_i \) are generated when time passes. This creates new data sequences from which the label \( y_i \) is characterized by the DNN. Therefore, this framework results in a direct data-fused-driven transition from sensor measurements to predicted behaviour (informed by the actual machine response data). Note that besides the implementation of sensors that measure primary attributes, it should be encouraged that more traditional sensor data that measure for example secondary rock attributes (e.g. throughput, material density) are also used to improve the prediction capabilities of the model. The predicted behaviour will be used as input for process control.

5 Behaviour based process control

From a machine performance perspective, the goal of, for instance, the ball mill is to maintain complex unit operating conditions. Maintaining is satisfied by containing operating conditions at values where the ball mill is optimized and can be measured by key performance indicators. Process control is often simulated in a model during the design phase with the use of control variables (Sbárbaro & del Villar, 2010). During operation the conventional process control then consists of translating secondary rock attributes based on an empirical incompletely validated relationship to predicted behaviour and process variables. Once the framework of this research is implemented in an operational system it will substantiate that an innovative way of process control is possible. This control is based on data assimilation of primary material attributes of the feed and secondary rock attributes. Additionally, it is informed by the actual plant response data.
From the fused data the behaviour (label $y_i$) of the machine is predicted by the model. This model-based behaviour is an indicator of how the ball mill would perform by processing this material, but this might not be the optimal process option for this material. The development in this pillar aims to find a fitting control setting (adjustment) which can be linked with this label and ensures that for the incoming material the optimal machine control settings is set. This could also mean that relative to the current setting, no change of control settings is needed. Once initialized in a running system a change in control settings can take place. This results in, for example, a better grindability in the ball mill. If not initialized, the material corresponding to the sensor responses will be processed with the ongoing control settings.

While processing the feed material, the actual plant performance is recorded. Comparison of the model-based predicted performance (and possible associated control setting change) and the actual performance can result in two outcomes. The predicted behaviour corresponds with the actual behaviour, and the actual behaviour differs from the predicted behaviour. The first case considers correct classification of the time series data and should be assumed in the early stages of research. However, it could also be due to a misclassification and a not found machine behaviour relation. Additionally, as mentioned in Wambeke, et al., (2017), it could also be because equipment performance measurements might start to drift as critical components are wearing out (e.g. liners in the ball mill). If due to these factors the behaviour by chance resulted in the predicted behaviour, classification was not correct. The second case indicates that the model had a misclassified label, because the accuracy of the model is not high enough. Another reason is that there is possibly a small difference in the type of materials and where this slight difference is key for a performance change.

To get a robust model, which is driven by behaviour caused by geological attributes it is key that the model (initially) makes mistakes, and that all data should be stored regardless the classification. After using the model some time, it can be retrained to improve the classification accuracy. In later stages, it is more important to do this for misclassified data sets only. In the future, the model could be extended with a machine learning system focused on the effect of its own critical components on equipment performance. This can provide an adjustment factor for the event’s label control settings to account for the state of the machine.

Future prospect is seen in providing new information about misclassified material to locally improve the geometallurgical model (Wambeke, et al., 2018), which will improve performance forecasts and more accurate and reliable resource models.

6 Focus areas for design realization

- The characterized material presented to the sensors might represent a blend of material, which might result in quick changes in sensor responses. Decisions should be made when a setting control change is required. For example, what to do in the case of a continuous change vs a discrete change in material.

- The moment of fused data analysis is important to consider in order to make the right process control decision. If the location of the material is still outside the plant, material can be blended, disregarded as ore or processed later to acquire a better plant behaviour. If the mate-
eral is within the comminution circuit, then decisions should have a direct (reactive) impact on process control, because this material will be processed next.
- Generating the fused data response may not be straightforward. The defined set of variables that characterize the process state are subject to each process and must be found in order to correctly characterize the process. Material type characteristic features might need to be identified before correct fused data can be generated.
- Construction of a database where sensor responses are related to performance might be challenging and depends on available data. Additionally, the appropriate CNN model should be selected by testing different deep neural networks. Possible future use could be an early awareness multiscale neural network (Wang, et al., 2016), where behaviour changes can be discovered even earlier.
- If a quantitative prediction of plant behaviour is not possible, predictions should be resorted to a more qualitative approach (low, medium, high performance).
- Validating the framework and predictions might need to rely on prior extensive metallurgical test work.

7 Conclusion and future outlook

Comminution circuit performance is likely to be influenced by the primary material attributes of the blended feed. These attributes can be measured by sensors and the data accordingly contain the geologically influenced behaviour. This implies incorporating direct data-fused-driven characterization into decision making to control machine performance in the comminution circuit. This promises a large potential to improve recovery and reduce energy utilization. Future decisions can be made on multiple continuous measured variables which are analysed together using time series event classification by a deep neural network. Additionally, comparing geometallurgical model and sensor-based behaviour predictions with actual plant behaviour can provide interesting information for resource model updating, what can extend the work of (Benndorf, et al., 2014) and (Wambeke, et al., 2018). Depending on the physical material location (stockpile or plant), early decisions can be made on different blending strategies or reclassification of material.

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The Use of Production Scheduling Analogs for Reconciliation of Mining Reserves

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ABSTRACT:

Reconciliation is a process that allows determination of the ability of a mining operation to produce the tonnage, grade and contained metal that were estimated in the ore reserve. This process consists on evaluating and correcting the sources of errors of tonnage and grades occurring in the temporal path from the estimation of resources up to the mill. In most mines there are two main sources of error: (i) inaccuracy in estimation of mineral resources and/or ore reserves (ii) inefficiency in the mining process to segregate ore and waste as planned (short range model) (Parker, H., 2012).

In most of mining operations there is a large temporal and operational gap between the estimation of block grades and tonnages and the corresponding reserves received at mill. Here the main issue is the variety of deviations occurring in all mining operations during the temporal gap between the predicted scheduling, based on the estimated reserves, and the real grades and tonnages measured at the mill.

There is a long reference of works, and mining practices, that try to quantify the deviations in order to minimize them. The main problem of any methodology remains in the temporal duration of that gap, i.e. the large is the gap between the estimation of block grades and tonnages and the corresponding reserves measured at mill, the more difficult is to identify the sources of the deviations.

In this work a new approach is proposed, consisting on simulating an intermediate production scheduling (grades and tonnages) at the mine production level, in order to characterize and correct the deviations obtained at the mill.

This approach is being developed in an underground mine and basically consists in two main steps: i) At the production haulage of an underground mine, the loaders will register the time of each discharge in the corresponding orepass. An individual device (Cell phone) will be used by each loader operator to register the temporal discharges; ii) Each temporal discharge record is associated with the metadata of the stope operated by the loader, essentially the estimated block grades and corresponding uncertainty. This near real time
measurements allows the temporal records of all loaders to be transformed in a temporal signal of grades and tonnages. This time scheduling of grades, tonnage and metals, can be considered an analog of the mill measurements, and becomes an important tool to fill the gap, between estimated reserves and mill measurements, and to correct local deviations.

The estimation of this intermediate analog scheduling, is obtained with a Gaussian mixture models of the simulated grades and attached uncertainty of the stopes (Neves et al, 2018). The production scheduling analogs are used to be compared with the real measurements of the mill, in order to be detected critical areas and periods regarding the mismatch between both.

This study is part of the H2020 Real Time Mine project and is being tested in Neves Corvo Mine.
Data exchange by WLAN and TTE in underground mining to a Supervisory Control And Data Acquisition system basing on OPC Unified Architecture

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ABSTRACT:

Data exchange and operation monitoring of underground mining activities is subjected to mobility of operation. The Horizon 2020 project – Real-Time-Mining deals with the continuously advancing production sites of mining with particular focus on ore mining. Automation and digitalization of mining operations increasingly necessitates the installation of infrastructure for data transmission and integration; the issue TU Bergakademie Freiberg and IBeWa Consulting Engineers deal within this project. Even at inactive parts of a mine, where accessibility is no longer possible to humans, sensors and data transmission technology is able to deliver safety relevant information for mine operation.

Wireless LAN is the predominant technology applied for mobile data exchange in underground mining. Automation requires uninterrupted exchange of data, making comprehensive coverage of a WLAN signal crucial. For spatially narrow sections, the application of leaky feeder cable proves to be feasible for minimizing installation effort, while providing a stable signal. For the underground mining industry, however, the requirements for surface and underground application of WLAN are diverging unfavorably. Demonstrated by an experimental test loop installed at the research and education mine Reiche Zeche, the paper points out the contradictionary motivation of network suppliers to increase bandwidth performance and enhance noise cancellation with that of underground mine IT responsible to realize holistic network provision with limited infrastructure to be replaced continuously along production.

At the same time, embedding digital entities from the field level to superordinate communication structures becomes easier and more powerful. For the incentive of TU Bergakademie Freiberg to create a feasible Supervisory Control And Data Acquisition solution for small scale mining activities, reduction of system engineering proved to be most essential. A siloing effect of enclosed vendor environments is observed from manufacturers and system integrators side, making interaction and integration of multi-vendor technology challenging. The emerging industrial communication architecture “OPC Unified Architecture”
splits for the first-time functionality from the data transport level. Thus, it allows realizing communication of field level entities on a multi-level basis simultaneously, i.e. Machine to Machine, Machine to Application and Machine to Cloud. Demonstrated by a newly developed SCADA application for mine control, the advantage of a common language for both, horizontal and vertical communication, is highlighted, reducing effort for system engineering significantly.

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Geotechnical parameter definition from machine performance measures for sonic drilling

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ABSTRACT:

Today, mine operators are confronted with smaller margins on the production of raw materials. In addition to that, receiving a license to operate from the community is not evident any more. Both reasons force mine operators to optimize their processes with respect to efficiency and environmental impact. A first step to make this optimization possible is collecting detailed and real-time information of all processes running in the mine. This information can then be used for decision making and control loops. Within the project ‘Real-Time Mining’ an integrated information collection, visualization and decision making concept has been developed. The work package ‘Sensors for Machine Performance Measurement’ is aiming at first quantifying the performance of cutting and sonic drilling machines, operated in the mine, in real-time. The second step is to correlate this performance measures to actual properties of the rock that is drilled or cut. This geotechnical information can be used instantly to optimize for example blasting designs or rock support strategies.

Eijkelkamp SonicSampDrill and the Institute for Advanced Mining Technologies of the RWTH University are working on methods and sensor technologies to quantify the performance of the cutting and drilling processes. Measurement While Cutting (MWC) and Measurement While Drilling (MWD) sensor systems have been made process specific and were installed on both lab and operational size equipment. Also initial tests with Acoustic Emission (AE) sensors have been executed for both processes. From the geotechnical perspective, the Unconfined Compressive Strength (UCS) was defined as the most important parameter to be made available in real-time during cutting or drilling. Therefore multiple test series have been executed in which multiple materials with different UCS values have been cut and drilled, resulting in initial correlations. More extensive Operator Assistance Systems and Condition Monitoring will certainly be future spin-offs of the research results.
1  Introduction

Since mining companies are facing increasingly complex ore bodies and increasing environmental awareness by society, efficiency optimization steps need to be taken. The value of detailed information about the ore body, in an as early as possible stage, is increasing rapidly. Therefore, a lot of effort is put into retrieving valuable information from all the stages of the mining process. This is preferably done from equipment that is already implemented in the process. Since drilling equipment is often the first equipment to touch the actual rock with ore potential, the drilling equipment can play a key role in retrieving valuable information about this rock, as soon as possible.

As a part of the European funded research project Real-Time Mining, the potential of determining geotechnical parameters from sensor-based performance data from a sonic drill rig has been investigated. Sonic drilling is a drilling technology, which combines rotational movement of the drill string, with vibrational movement at a frequency of up to 150 Hz. The research focusses on defining empirical algorithms to correlate different sensor type’s outputs to pre-defined geotechnical parameters. Since the project focusses on underground mining, geotechnical parameters with an importance for blast design and local rock support strategies are considered.

2  Selection of most relevant geotechnical parameters

There are different classification systems for rocks used in mining. These classification systems bundle relevant geotechnical parameters that are relevant for the design and construction of excavations like tunnels, mine works and foundations. Since the establishment of the first system in the 1946s, numerous other systems have been developed and improved. For example, the Rock Mass Rating (RMR) system from (Bieniawski, 1976), the Mining Rock Mass Rating (MRMR) system from (Laubscher, 1990), the Q system from (N. Barton, 1974) and the Geological Strength Index (GSI) from (Brown, 1997). All of these ranking systems have one thing in common: They count the Unconfined Compressive Strength (UCS) as a part of the most influencing rock parameters. The UCS is also considered as one of the most important fresh rock geotechnical parameters for the task of blast design and local rock support strategies. A big advantage of this parameter is its simple determination. In addition to the UCS, the Brazilian Tensile Strength (BTS) was also taken into the analysis. The reason for this was that this parameter gives access to defining a Brittleness Index (BIX) (Altindag 2003). Furthermore, there is a known relation between the Drilling Rate Index (DRI) for rotary drilling and the BIX, why it makes sense to include it. (Soyer, 2011)

3  Data Acquisition

Conditioned field tests have been executed to create and expand a dataset on which the mentioned correlation analysis is applied. During the tests, a sonic drill rig (SonicSampDrill, 2019) was used to drill multiple holes in rock blocks of different rock types with known UCS and BTS figures.
During the tests, the following conditions have been pursued:

- The main settings: Sonic frequency, pull down force and rotation speed, are controlled.
  - The “optimal” configuration of these settings for each rock type is sought by the drilling operator.
  - The configuration is varied around the optimum for each acquisition sequence.
  - The configuration is kept constant throughout the acquisition sequence.
- At least 240s of data (at 10S/s, so 2400 samples) is acquired for each setting configuration for repeatability warranty.
- The same amount of setting configurations, or boreholes, are done for each rock type to warrant a comprehensive dataset.

During these tests, the sonic drill rig is fitted with a Measurement While Drilling (MWD) system to measure the machine performance parameters. The sonic drill rig is also equipped with Acoustic Emission (AE) sensors, to measure the non-machine-bound acoustic emissions (vibrations in the frequency range of 120 kHz to 500 kHz) from the breaking/grinding process during drilling. The test set-up is schematically displayed in Figure 1.

![Figure 1: Schematic overview of the test set-up.](image)

AE is a solid-state acoustic emission analysis in which transient elastic waves are evaluated predominantly in the ultrasonic range above 20 kHz. Contrary to most ultrasonic methods, this method is not based on an active, emitting method, but on a purely passive, receptive method in which so-called burst events are received by a sensor and evaluated using suitable analysis methods. The evaluation of these discrete vibration signals can be carried out in the time domain or in the frequency domain, whereby statistical methods and characteristic values as well as so-called burst detection methods can be applied in the time domain. The burst detection methods are methods, which record the individual burst events and process them statistically. In the frequency domain, spectral, envelope or cepstrum analyses are used. In addition, analysis methods in the time-frequency domain can also be used. Examples are waterfall diagrams or order analyses. (Philipp, et al., 2017) (C. I. Klein, 2018)

The first AE analysis methods originate from bearing and transmission diagnostics and have been increasingly used since the availability of ever more powerful analog-to-digital converters (ADC) and computer processor units (CPU), as well as inexpensive and fast storage media. These are necessary because with sampling rates of two MegaSamples or more, the oscillations are recorded via different sensor types, such as piezoelectric sensors. With piezoelectric sensors, a pressure-dependent / deformation-dependent charge shift of special crystals and ceramics is used, resulting in
a measurable electrical voltage, also called piezoelectric effect. In contrast to piezoelectric structure-borne sound sensors, in which the piezoelectric effect is triggered by a flywheel mass, AE sensors do not use a flywheel mass. Due to the direct contact of the sensor with the surface of the specimen and the rapid deformability of the piezo material, it is possible to record high-frequency surface vibrations. In bearing and gear diagnostics, these vibrations are caused by damage to the running surfaces, while during drilling they are caused by direct interaction between the tool and the rock. The break-up of the grain structure and the shredding phase of the cuttings trigger vibrations that can be absorbed along the drill string. Due to the limited release of energy during the fracture event and a lossy propagation of the vibration signal, the amplitude of the vibration loses intensity as the propagation progresses. The propagation is negatively influenced especially by gaps and boundary crossings of connections. This makes an application of AE sensors in the direct vicinity of the event source necessary, especially for low-energy events, such as incipient bearing damage. (Philipp, et al., 2017) (C. I. Klein, 2018) (Christoph Büschgens, 2015) (F. D. Boos, 2015)

The 9 parameters that are acquired from the MWD sensor system are displayed in Table 1. All these parameters were logged time based at a rate of 10 Hz.

Table 1: The list of logged parameters by the MWD system.

<table>
<thead>
<tr>
<th>Nr.</th>
<th>Parameter</th>
<th>Unit</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Time</td>
<td>hh:mm:ss.ms</td>
<td>1 ms</td>
</tr>
<tr>
<td>2</td>
<td>Depth</td>
<td>m</td>
<td>0.1 m</td>
</tr>
<tr>
<td>3</td>
<td>Advance speed</td>
<td>m/h</td>
<td>0.1 m/h</td>
</tr>
<tr>
<td>4</td>
<td>Rotation speed</td>
<td>rpm</td>
<td>1 rpm</td>
</tr>
<tr>
<td>5</td>
<td>Bit Force</td>
<td>N</td>
<td>0.5 Bar</td>
</tr>
<tr>
<td>6</td>
<td>Torque</td>
<td>Nm</td>
<td>0.1 Nm</td>
</tr>
<tr>
<td>7</td>
<td>Sonic pressure</td>
<td>Bar</td>
<td>0.5 Bar</td>
</tr>
<tr>
<td>8</td>
<td>Sonic accelerati-</td>
<td>g</td>
<td>1 g</td>
</tr>
<tr>
<td>9</td>
<td>Sonic frequency</td>
<td>Hz</td>
<td>0.1 Hz</td>
</tr>
</tbody>
</table>

The AE signals are sampled at 1 MHz and simultaneously, on a separate channel, a trigger signal of the MWD system is recorded so that both systems are synchronized. To decrease the amount of maladjustments of the gain, three preamplifier were connected parallel. The AE sensor was mounted on the swivel of the drill rig, the nearest position for cable bound measuring. A wireless signal acquisition on the drill string was tried out, but could not be functionally implemented because the forces on the drill string were too great.
Figure 2: Measuring positions on the drill rig, on the Swivel on the left and the wireless measuring box on the right.

For these tests, blocks from the rock types stated in Table 2 are buried in a test field. It is assumed that the different rock blocks are perfectly homogeneous, therefore the laboratory UCS and BTS test results are extrapolated for the whole block. From the UCS and BTS values, the Brittleness Index (BIX) is calculated by dividing the UCS by the BTS value (Altindag, 2003) for every rock type.

Table 2: The 7 rock types with their average UCS, BTS and calculated BIX values.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prefab Concrete</td>
<td>39.5</td>
<td>3.7</td>
<td>10.7</td>
</tr>
<tr>
<td>2</td>
<td>Poured Concrete</td>
<td>56.2</td>
<td>2.8</td>
<td>20.1</td>
</tr>
<tr>
<td>3</td>
<td>Limestone</td>
<td>171.6</td>
<td>7.1</td>
<td>24.2</td>
</tr>
<tr>
<td>4</td>
<td>Granite</td>
<td>172.5</td>
<td>9.5</td>
<td>18.2</td>
</tr>
<tr>
<td>5</td>
<td>Gneiss</td>
<td>209.8</td>
<td>14.1</td>
<td>14.9</td>
</tr>
<tr>
<td>6</td>
<td>Limestone Bian-</td>
<td>103.4</td>
<td>7.1</td>
<td>14.5</td>
</tr>
<tr>
<td>7</td>
<td>Limestone Rose</td>
<td>92.5</td>
<td>8.7</td>
<td>10.7</td>
</tr>
</tbody>
</table>

4 Data Filtering

Data filtering is one of the most important signal processing tasks that must be performed in preliminary evaluation. It reduces errors and misinterpretation of the data. This was necessary for all datasets because the measuring system consisted of different individual systems. Although a trigger signal synchronized the systems, there were time sections in the signal without measurement because the trigger signal was not coupled to the control of the drill rig. For this reason, it was necessary to filter, because otherwise the death times would influence the evaluation negatively. However, system limits can also lead to filtering, as can happen with Acoustic Emission when unexpected-
ly high amplitudes in the measurement signals reach the non-linear saturation range of the preamplifier. This will adversely affect or even cut the signal and leads to misinterpretation. MWD data

Filtering of the data is required to extract effective drilling activity from the logs, as logging starts before the drill bit engaged the rock. Also, in a few holes drilling paused temporarily. Also, filtering is required for the end of hole to take care of breaking through the base of the blocks and entering the soft sands below, stopping drilling and pulling the string.

The approach taken is based on the pulldown pressure (cut off value) and on the rotation speed (cut off value). The filtering process uses robust estimates of the central tendency, the median, and the Mean Absolute Deviate (MAD) as a robust estimator of the standard deviation. Data outside of the 1.5 MAD band around the median is rejected. A two-stage sequential filter provided acceptable data that is nearly free of the adverse effects.

After these filtering steps, the 10 Hz measurements are averaged over a depth interval of 10 cm to convert the resolution of the acquired data set to the resolution of the UCS and BTS laboratory results (The UCS tests are executed on samples with an approx. height of 10 cm). This averaging step results in the reduction of the amount of data points and the exclusion of outliers.

For the AE measurements, it was also necessary to find a workflow to separate the measurement data during the drilling process from downtimes. In addition, the measurement data also had to be checked to see whether the correct gain had been set on the preamplifier. Since the excitation of AE bursts and their amplitude are not directly related to the UCS of the rock, the correct choice of amplification can only be determined empirically by experiments. In order to increase the amount of usable measurements, three amplifiers were connected parallel so that the sensor signal could be recorded with different amplifications. For a better interpretation and comparison of the AE result with the MWD results, time intervals of one tenth of a second were also selected for generating of statistical characteristic values.

5 The data set

The size of the MWD data set and the distribution over the different rock types is displayed in Table 3.

<table>
<thead>
<tr>
<th>Nr.</th>
<th>Rock Description</th>
<th>Covered drilled distance [m]</th>
<th>Amount of raw data points</th>
<th>Amount of data points after filtering</th>
<th>Amount of data points after filtering and averaging</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prefab Concrete</td>
<td>17,30</td>
<td>15896</td>
<td>6438</td>
<td>56</td>
</tr>
<tr>
<td>2</td>
<td>Poured Concrete</td>
<td>12,53</td>
<td>12241</td>
<td>9127</td>
<td>78</td>
</tr>
<tr>
<td>3</td>
<td>Limestone</td>
<td>13,38</td>
<td>28270</td>
<td>14514</td>
<td>53</td>
</tr>
<tr>
<td>4</td>
<td>Granite</td>
<td>19,61</td>
<td>65302</td>
<td>15666</td>
<td>16</td>
</tr>
<tr>
<td>5</td>
<td>Gneiss</td>
<td>0,83</td>
<td>2868</td>
<td>2053</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>Limestone Bian-</td>
<td>5,56</td>
<td>15425</td>
<td>12375</td>
<td>37</td>
</tr>
<tr>
<td>7</td>
<td>Limestone Rose</td>
<td>6,40</td>
<td>12315</td>
<td>9300</td>
<td>44</td>
</tr>
</tbody>
</table>

Table 3: The size of the data set of the MWD data.
6 Data Analysis

For the definition of the empirical algorithms to correlate different sensor types outputs to the geotechnical parameters, 3 correlation approaches are used:

1. Specific Energy approach (Based on the MWD data set)
2. Machine Learning approach (Based on the MWD data set)
3. Acoustic Emission approach (Based on the AE data set)

Each approach will be introduced shortly.

6.1 Specific Energy approach

The specific energy is a generally used parameter to quantify the used energy for a certain amount of work done. For drilling, the specific energy is defined as the amount of energy used to drill a certain distance (which can be calculated to a volume, together with the surface area of the drill bit), which leads to the unit J/m³ (Teale, 1964). Therefore it is a measure for the interaction between the drill rig and the rock. For rotary drilling correlations between Specific Energy and UCS are defined (Itakura., 2012). It is important to consider that the exact definition of specific energy is different for each system and possibly different for each case.

For this case, the energy is supplied by the three actors of sonic drilling: rotational movement, vibrational movement and bit force. The energies used for both the rotational movement and the vibrational movement are calculated from the readings of hydraulic oil flow and pressure sensors. For the rotational movement, the rotation speed (rad/s) is calculated from the hydraulic flow (m³/s) and the torque (Nm) is calculated from the hydraulic pressure (Pa) (by calibrated system specific conversion algorithms). The applied power is then calculated using equation 1.

\[ P = \tau \omega \]  

\( P = \) power in J/s  
\( \tau = \) torque in Nm  
\( \omega = \) angular velocity in rad/s

The applied power via the vibrational movement is estimated directly from the hydraulic flow and pressure readings using equation 2.

\[ P = Q H \eta \]  

\( P = \) power in J/s  
\( Q = \) flow of hydraulic fluid through pump in m³/s  
\( H = \) hydraulic head created by the pump in Pa  
\( \eta = \) pump efficiency factor

Both power values are then summed for each data point to a total power figure. From this total power figure, the energy can be calculated by multiplying with the time interval. Finally, the Specific Energy can then be calculated by dividing the energy by the volume of material drilled (combination of the diameter of the hole and the drilled distance within the time interval). The Specific Energy figure is then completed by adding the Bit Force Specific Energy factor (Teale 1964):
\[ E_{sp\ Bit\ Force} = \frac{F}{A} \]  

\( E_{sp\ Bit\ Force} = \text{Specific Energy Bit Force in J/m}^3 \) (Equivalent to N/m²)
\( F = \text{Bit Force in N} \)
\( A = \text{Surface area of drill bit in m}^2 \)

6.2 **Machine Learning approach**

Before feeding the MWD data set to a machine learning algorithm, a set of features is extracted for each increment and added to the data set: mean, sum, inverse and degree-2 polynomials. Then a Support Vector Regression (SVR) algorithm is applied to define the performance.

6.3 **Acoustic Emission approach**

The AE data is evaluated both in the time domain and frequency domain. The methods used in the time domain of the AE signal to evaluate the results of the field test are burst detection and statistical characteristic value methods. The time window for the characteristic values used in the evaluation is one second, which corresponds to one million data points at the set sampling rate.

With evaluation methods in the frequency spectrum of the signal, the signal is broken down into various sinusoidal oscillations of different frequencies by means of Fast Fourier Transformations (FFT). Like the time domain, the data is evaluated with statistical characteristic values. But also, qualitative methods for the determination of the bandwidth of the excited frequencies or the localization of strongly excited frequencies are applied.

![Figure 3: Possible evaluation methods for the acoustic emission](Nienhaus, et al., 2012)
7 Results

In this chapter, the results of the three approaches will be presented.

7.1 Specific Energy approach

In Figure 4 three scatterplots are displayed, showing the relation between the Specific Energy and the geotechnical parameters UCS, BTS and BIX. A linear trend line is fitted to approach the correlation between the Specific Energy and the geotechnical parameters. A linear relation is chosen because the average Specific Energy value per rock type shows a clear linear trend. The defined linear relation is used as a model to predict the geotechnical parameters based on the calculated Specific Energy.

![Figure 4: Scatter plots representing the relation between Specific Energy calculated from the MWD data and the geotechnical parameters UCS, BTS and BIX.](image)

In Figure 5 three box plots are displayed showing the performance of the Specific Energy based prediction of the geotechnical parameters (by applying the defined linear relation to the full data set). The performance is quantified as the relative error, which is the absolute error of each predicted value divided by the true value. The green line in the box plots represents the median of the prediction errors, the bottom and top of the box represent the 1st and 3rd quartile, the end of the whiskers represents the minimum and maximum errors (excluding outliers). The prediction errors outside a window of 1.5 times the height of the box, measured from the upper and downside of the box, are considered outliers.

![Figure 5: Box plots showing the performance of the Specific Energy based prediction of the geotechnical parameters.](image)
A comprehensive statistical overview of the prediction performance of the Specific Energy model is displayed in Table 4. The representation is split in absolute residuals and relative residuals. The relative residuals are relative to the true value for the geotechnical parameter.

Table 4: The statistics (Standard Deviation, Mean Signed Deviation, Median Absolute Deviation, P5, Median, P95, relative MAD, relative P5, relative Median and relative P95) showing the performance of the Specific Energy based prediction of the geotechnical parameters UCS, BTS and BIX.

<table>
<thead>
<tr>
<th></th>
<th>Absolute Residuals</th>
<th>Relative Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>STDev MSD MAD P5 Med P95</td>
<td>MAD P5 Med P95</td>
</tr>
<tr>
<td>UCS</td>
<td>34.0 1155.3 18.7 -37.7 -9.9 68.7</td>
<td>24.8% -65.7% - 40.0%</td>
</tr>
<tr>
<td>BTS</td>
<td>1.9   3.4  1.5 -2.1 -0.4 3.7</td>
<td>26.4% -70.5% -9.7% 43.0%</td>
</tr>
<tr>
<td>BIX</td>
<td>5.0   25.3 4.8 -6.4 -1.2 7.2</td>
<td>25.6% -60.2% -6.8% 29.6%</td>
</tr>
</tbody>
</table>

7.2 Machine Learning approach

In Figure 6, three box plots are displayed showing the performance of the MWD data-based Machine Learning Algorithm prediction of the geotechnical parameters. The performance is quantified as the relative error, which is the absolute error of each predicted value divided by the true value. The green line in the box plots represents the median of the prediction errors, the bottom and top of
the box represent the 1st and 3rd quartile, the end of the whiskers represents the minimum and maximum errors (excluding outliers). The prediction errors outside a window of 1.5 times the height of the box, measured from the upper and downside of the box, are considered outliers.

![Box plots showing the performance of the MWD data based Machine Learning Algorithm (Support Vector Regression) prediction of the geotechnical parameters UCS, BTS and BIX.](image)

A comprehensive statistical overview of the MWD data-based prediction performance of the Support Vector Regression is displayed in Table 5. The representation is split in absolute residuals and relative residuals. The relative residuals are relative to the true value for the geotechnical parameter.

Table 5: The statistics (Standard Deviation, Mean Signed Deviation, Median Absolute Deviation, P5, Median, P95, relative MAD, relative P5, relative Median and relative P95) showing the performance of the MWD data based Machine Learning Algorithm (Support Vector Regression) prediction of the geotechnical parameters UCS, BTS and BIX.

<table>
<thead>
<tr>
<th></th>
<th>Absolute Residuals</th>
<th>Relative Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>STDev</td>
<td>MSD</td>
</tr>
<tr>
<td>UCS</td>
<td>13.5</td>
<td>183.2</td>
</tr>
<tr>
<td>BTS</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>BIX</td>
<td>1.3</td>
<td>1.7</td>
</tr>
</tbody>
</table>
7.3 **Acoustic Emission approach**

As with the specific energy and machine learning evaluation, an attempt was also made to use the UCS, BTS and BIX for the statistical evaluation of the AE signals. As an example, the Root Mean Square (RMS) of the signals of 0.1 second intervals has been assigned to the geotechnical rock values in Figure 7. It can be seen that no linear dependence of the statistical characteristic value can be drawn to the geochemical rock characteristics.

![Figure 7: Scatter plots representing the relation between RMS calculated from the AE data and the geotechnical parameters UCS, BTS and BIX.](image)

Figure 8 shows three box with the performance of the Acoustic Emission prediction model. The performance is quantified as the relative error, which is the absolute error of each predicted value divided by the true value. The red line in the box plots represents the median of the prediction errors, the bottom and top of the box represent the 1st and 3rd quartile, the end of the whiskers represents the minimum and maximum errors (excluding outliers). The prediction errors outside a window of 1.5 times the height of the box, measured from the upper and downside of the box, are considered outliers. In this case, a lot of outliers could be identified.
Figure 8: Three box plots showing the performance of the Acoustic Emission based prediction of the geotechnical parameters UCS, BTS and BIX.

As before, another comprehensive statistical overview of the prediction performance of the AE model is displayed in Table 6. The representation is split in absolute residuals and relative residuals. The relative residuals are relative to the true value for the geotechnical parameter.

Table 6: The statistics (Standard Deviation, Mean Signed Deviation, Median Absolute Deviation, P5, Median, P95, relative MAD, relative P5, relative Median and relative P95) showing the performance of the RMS based prediction of the geotechnical parameters UCS, BTS and BIX.

<table>
<thead>
<tr>
<th></th>
<th>Absolute Residuals</th>
<th>Relative Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>STDev</td>
<td>MSD</td>
</tr>
<tr>
<td>UCS</td>
<td>48</td>
<td>-0</td>
</tr>
<tr>
<td>BTS</td>
<td>2.8</td>
<td>-0</td>
</tr>
<tr>
<td>BIX</td>
<td>2.5</td>
<td>0</td>
</tr>
</tbody>
</table>

The previous results are part of the statistical method in the time domain of the AE Signal and an attempt was made to calculate expected values by a linear regression, which were then compared with the results, similar to the procedures with the MWD system. Since no random linear correlation could be found, the results of the further investigations are listed below.

The methods used in the time domain of the AE signal to evaluate the results of the field test were burst detection and statistical characteristic value methods. The time window for the characteristic
values used in the evaluation is one second, which corresponds to one million data points at the set sampling rate.

The following figures present a selection of statistical parameters that were used to analyse the AE data. Figure 9, however, shows the root mean square (RMS), i.e. the square average of the AE signal, also referred to an interval of seconds. All presented results are adjusted, so that different pre-amplification have no influence on the signal characteristics.

![Comparison of RMS per Second [Bianco and Granite]](image)

![Comparison of RMS per Second [Rosé and Concrete]](image)

**Figure 9: Comparison of RMS values as a function of the AE signal**

Figure 10 shows two graphs with the statistical characteristic Kurtosis formed per second of the AE signal. In the upper graph, the Carrara marble and the granite block are plotted against each other while the lower graph shows the comparison between the kurtosis values of the Aurore marble and the concrete. Kurtosis is a measure of the curvature of an empirical frequency distribution.

Table 7 shows the average number of bursts recorded for a selection of the rocks. For both, the granite block and the Aurore Rosé marble are very close together. Only the concrete and Carrara marble blocks, which have comparatively high burst excitations, provide clearer results. These burst events also occur more evenly than with granite or Aurora marble.
Table 7: Average number of bursts

<table>
<thead>
<tr>
<th>Rock Samples</th>
<th>Ø Bursts per Second</th>
<th>Empirical coefficient of variation $\nu = \frac{\sigma}{\mu} \times 100$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concrete</td>
<td>229</td>
<td>21,42</td>
</tr>
<tr>
<td>Marble Bianco</td>
<td>Carrara 443</td>
<td>20,29</td>
</tr>
<tr>
<td>Marble Rosé</td>
<td>Aurore 65</td>
<td>98,53</td>
</tr>
<tr>
<td>Granite</td>
<td>61</td>
<td>62,43</td>
</tr>
</tbody>
</table>

Figure 10: Comparison of kurtosis values as a function of the AE signal

With evaluation methods in the frequency spectrum of the signal, the signal is broken down into various sinusoidal oscillations of different frequencies by means of Fast Fourier Transformations (FFT). Similar to the time domain, the data can be evaluated with statistical characteristic values. But also qualitative methods for the determination of the bandwidth of the excited frequencies or the localization of strongly excited frequencies are possible. Figure 11 shows four frequency spectra of the individual rocks. The frequency response curve of the sensor can be seen well in the spectrum of the two marble sorts and the concrete. All graphs show a local maximum at 100 kHz and increasing amplitudes in the range between 200 kHz and 350 kHz. Only the granite block excites, atypically in comparison with the three other frequency spectra, in the low-frequency range between 100
kHz and 200 kHz amplified frequencies. Ranges above 500 kHz cannot be examined due to the sampling rate of a MegaSample. The Nyquist Shannon sampling theorem states that recording must be at least twice the sampling frequency of the highest expected frequency.

Figure 11: Comparison of the frequency spectra of all rocks

7.4 Combined results

In Table 8, the statistics of the prediction performance of the geotechnical parameters by the Specific Energy model, the support Vector Regression and the Acoustic Emission model are combined.

Table 8: Combined statistics of the prediction performance of the geotechnical parameters by the Specific Energy model, the Support Vector Regression and the Acoustic Emission model.

<table>
<thead>
<tr>
<th>Relative Residuals of the Specific Energy model prediction</th>
<th>Relative residuals of the Support Vector Regression prediction</th>
<th>Relative residuals of the Acoustic Emission model prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAD</td>
<td>P5</td>
<td>Median</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>UCS</td>
<td>24.8%</td>
<td>-</td>
</tr>
<tr>
<td>BTS</td>
<td>26.4%</td>
<td>-</td>
</tr>
<tr>
<td>BIX</td>
<td>25.6%</td>
<td>-</td>
</tr>
</tbody>
</table>
8 Discussion

It should be noted that for all the analyses done, the average laboratory results for the UCS and BTS are assumed as the absolute true values for the whole rock block. However, the standard deviations of the laboratory results, as displayed in Table 9, show that there is an amount of variability within the rock block as well. Furthermore, the scale of the laboratory test (10 cm sample for the UCS test) is expected to be significantly different from the scale of the fracturing process in the rock while drilling (probably mm scale). On top of these errors, the laboratory test procedure itself contains an error as well. These errors related to the geotechnical validation are not considered during these analyses, but it is evident that they are affecting the performance results to a yet unknown extent.

Table 9: Table showing the average results and the standard deviation of the geotechnical laboratory tests.

<table>
<thead>
<tr>
<th>Nr.</th>
<th>Rock description</th>
<th>Average UCS [Mpa]</th>
<th>σ UCS</th>
<th>Average BTS [Mpa]</th>
<th>σ BTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prefab Concrete</td>
<td>39.5</td>
<td>6.4</td>
<td>3.7</td>
<td>0.3</td>
</tr>
<tr>
<td>2</td>
<td>Concrete</td>
<td>56.2</td>
<td>2.8</td>
<td>2.8</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>Limestone</td>
<td>171.6</td>
<td>0.4</td>
<td>7.1</td>
<td>1.2</td>
</tr>
<tr>
<td>4</td>
<td>Granite</td>
<td>172.5</td>
<td>22.9</td>
<td>9.5</td>
<td>0.2</td>
</tr>
<tr>
<td>5</td>
<td>Gneiss</td>
<td>209.8</td>
<td>31.1</td>
<td>14.1</td>
<td>0.9</td>
</tr>
<tr>
<td>6</td>
<td>Limestone Bianco</td>
<td>103.4</td>
<td>1.9</td>
<td>7.1</td>
<td>0.6</td>
</tr>
<tr>
<td>7</td>
<td>Limestone Rose</td>
<td>92.5</td>
<td>2.0</td>
<td>8.7</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Another issue that should be noted is that the calculated Specific Energy in this analysis is not the Effective Specific Energy (Itakura., 2012). This means that it is not the effective amount of energy that is used to cut and grind a certain volume of rock, excluding losses. This is a result of the fact that not all energy transfer factors for the sonic drilling system have been defined yet. The currently calculated specific energy seems to incorporate variable losses in the drilling process, which reduces the strength of the correlation with the geotechnical parameters of the rock. It is expected that the performance of the model improves with the implementation of accurate energy transfer factors.

A final note should be made from the fact that there is limited data available from drilling in the Gneiss rock. This is a result of issues with the stabilization of the irregularly shaped Gneiss blocks in the soil in the test field. It is decided to leave out the data of the drillings during which movement of the block is noticed.

8.1 AE Results

Although no linear correlation between the geotechnical rock characteristics and the statistical methods could be found, the results show that different approaches to AE analysis can be used to capture different rock types/strengths during the drilling process. A total of 40 different statistical characteristic values were investigated. And it turned out that different rocks responded differently well to the characteristic values. The average burst events per second listed in
Table 7 show that differentiating materials with burst detection alone is not sufficient. Although concrete and Carrara marble can be distinguished from granite and Aurore marble in a pure burst analysis, it is not possible to distinguish between Aurore marble and granite. Both signals have on average very similar burst excitations of 60 - 65 bursts per second. The empirical coefficient of variation of both rocks, a dimensionless scattering measure, shows that the values above 50 % deviate from the empirical mean value. For Aurore marble, almost all values (98.53%) deviate significantly from the mean value. This difference occurs when zones with high burst activity meet zones with particularly low burst activity. On average, an average value is obtained, which, however, is not representative enough for a material classification alone. If the bursts are related to the actual compressive strength of the rocks, it appears that more compressive materials produce fewer bursts during a drilling process. However, this is contradicted by the expected compressive strength of the two marble variants. As long as the drill cores are not analysed, it is difficult to make a statement because the sample size is too small.

For statistical parameters, such as the RMS, the significance of the parameter is based on the raw signal generated by the tool and rock. Depending on the geometry of the component, other characteristic values can provide more target-oriented results in related rocks. All drillings were carried out with the same drill bit, which was newly installed at the factory on the first day. As Figure 4 shows, it is hardly possible to distinguish the rocks with kurtosis. A differentiation of the rocks is visually possible via the RMS graphs, but the imaginary regression lines are very close to each other, which makes a clear separation, especially caused by fluctuations in the composition of the natural rock, very difficult.

Figure 11 shows that different frequencies are excited by different materials which, at least within the limited sample size, support the theory that it is possible to distinguish rocks by different excitations of the frequency spectrum. However, it is necessary to study other types of rocks, especially related rocks, to determine the extent to which rocks can be differentiated using AE signals. Basically, it should be noted that an evaluation in the frequency spectrum requires an increased computing effort, since the AE signals must be decomposed into individual sinusoidal oscillations by Fast Fourier transformations. This means that timely detection cannot be guaranteed in very time-critical applications.

9 Conclusions

The performance of the Specific Energy model is poor, with the best performance of the BIX prediction with an relative error of +/- 60% (90% confidence level). It seems that there is significant noise in the calculated Specific Energy values for the 10 cm intervals, because of changing effectiveness of the process. Improvement of the calculation of the actual energy transferred to the rock, i.e. the definition of the Effective Specific Energy, could improve the prediction performance at this scale.

The Support Vector Regression algorithm is performing much better with an error of +/- 15% for the BIX, and +/- 20% for the UCS and BTS (all with a 90% confidence level). The relative MAD of about 4/5% shows that the error of the middle 50% of the predictions is rather low.
From both the Specific Energy approach and the Machine Learning approach, the BIX comes out as the best predictable geotechnical parameter. More fundamental physical research is required to validate and explain this outcome. However, it seems not very surprising that the drilling process is majorly influenced by a brittle versus ductile behaviour. The relation between the Drilling Rate Index (DRI) for rotary drilling and the BIX has already been described in literature (Soyer, 2011)

Previous investigations have shown that AE analysis methods can support cutting and drilling process monitoring systems as supplementary systems. It is possible to substitute certain sensors, such as structure-borne sound sensors, with the higher resolution so that the number of sensors and thus parallel measuring chains can be reduced. In cutting tests, the higher resolution of the AE signals also allowed conclusions to be drawn about fractures and other disturbances in the tested materials that had not previously been detected in the drilling tests. This can be due to the rotating and percussive mode of operation of the drilling equipment used, whereby the additional movement and force introduction superimpose these signal components, or to the drilling process itself, whereby the resolution of the AE sensors is impaired by the slower removal of the cuttings compared to most cutting methods. This must be determined in further experiments using rotating drilling tests without additional impact damage.

However, it was also shown that material and boundary layer detection with acoustic emission is possible within the framework of the tested rocks, as was also initially possible during the cutting tests. The presented AE analysis methods show that only a combination of the methods allows a satisfactory differentiation, since the rocks used have different AE signal components, which deliver different good results with the individual methods in the time and frequency spectrum. The analysis methods in the frequency spectrum in particular are very computationally and time-intensive, which places high demands on the CPUs of the data processing units. This leads to problems in very time-critical applications, as the required computing power requires high investment costs or, under certain circumstances, is currently insufficient. With increasing available computing power and decreasing costs for CPUs, this problem can probably be solved in the next few years.

By using AE it is possible to make drilling processes more transparent through higher resolution and material and boundary layer detection, thereby developing systems that support the machine operator or even lead to autonomously controlled drilling processes. But also digital drill cores, which can be generated in the running process by means of the AE and other drilling data, represent an additional gain for the drilling process. Nevertheless, it is necessary to validate the methods under laboratory conditions and to develop suitable algorithms by further experiments on different rocks and a multitude of measurement series. The maximum borehole depth must also be determined for the use of the wired measuring point. It also requires revised sensors and measuring modules that can withstand the harsh operating conditions and can be mounted on the drill pipe. In particular, data transmission from the sensor in the borehole to data processing or terminal equipment on the surface still has to be solved by suitable means. Nevertheless, the results obtained so far allow transferability to real operating wells, so that continuation of the tests and a later application of the AE sensors in drilling rigs can be regarded as desirable. A reliable evaluation of the results is only possible under laboratory conditions with a high number of measurement series and statistical evaluation and at the same time a high effort for the rock science of the samples used.
Overall, the Support Vector Regression Algorithm is currently the best performing predictor for the defined fresh rock geotechnical parameters (UCS, BTS and BIX), applied on sensor-based performance data of a sonic drill rig.

10 Recommendations

Based on the discussion and conclusions of this paper, the following list of recommendations can be compiled:

1. The complete set of energy transfer terms in the sonic drilling process should be determined to define the Effective Specific Energy. The relation between the geotechnical parameters (UCS, BTS and BIX) and the Effective Specific Energy should be re-modelled and the performance of the prediction reviewed.
2. It should be investigated what the drivers of the defined outliers are. This will improve the understanding of the prediction performance.
3. A fundamental physical model of the sonic drilling process should be created to generate new and improved features for all correlation approaches. Furthermore, this physical model can be used to validate conclusions drawn from the empirical analysis. For example, the conclusion of the BIX having the strongest relation with the drilling performance can be validated with this model.
4. For AE further tests with different rocks are necessary to create an AE rock fingerprint database. Tests should also be carried out without impact activation in order to avoid the influence of this additional movement and energy input.

REFERENCES


An Approach to Optimize Underground Mining Processes by the Use of Real-Time Data

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ABSTRACT:

The responsible and sustainable mining of complex deposits, especially in the EU countries, comes along with enormous challenges for today’s mining companies. Characteristics of small mines such as low investment, incomplete exploration of deposits and rapidly changing conditions result in a demand for flexible and low-cost extraction systems. In particular, the use of such systems in combination with real-time data will improve fast and flexible decision making in daily operations. This results in better productivity, improved resource utilization and reduced energy consumption.

This paper aims at integrating real-time data into a managing system for underground mining processes. For this reason, basic mining processes are reviewed and essential process steps are identified. Subsequently, the use of real-time data in these process steps is analysed and the results are used to formulate new concepts for these processes. Results of the investigations show, that within all underground mining process steps, the blast design and the roof support show high potential for efficiency improvements. However, to unlock the whole optimization potential in underground mining, the link between all processes in the mine-to-mill operation is essential. The concepts presented in this paper address these criteria and give an outlook on future technical solutions.
1 Introduction

The Horizon 2020 Real-Time Mining project aims at the development of a real-time framework to decrease environmental impact and increase resource efficiency in the European raw material extraction industry. The goal is to shift from discontinuous processes to real-time continuous process control and optimization. Within the project, 13 European project partners analyse the optimization potential in exploration, resource modelling, mine planning and mine operation, which can be unlocked with the help of real-time data. The Institute of Mineral Resources Engineering (MRE) of RWTH Aachen University is hereby focused on concepts for the optimization of mine planning and operation. This short paper addresses the real-time optimization of underground mining processes, aiming at a reduction of energy consumption and costs and the increase of resource efficiency by maximizing deposit exploitation.

Optimization potentials have already been discovered by industry, leading to several approaches and marketable solutions like ventilation-on-demand systems, drill pattern optimizers and more energy-efficient equipment [Cervinka et al. 2010, Babu et al. 2015, Paraszczak et al. 2014]. However, the potential of improvement is detected in the optimization of blast design [Acuña et al. 2016]. Apart from that, the industry is still lacking a holistic optimizer solution, which takes into account the whole underground mine-to-mill process. Therefore, new concepts, which use the connection between subprocesses for a more holistic approach, are required. The aim is to find the most cost- and energy-efficient configurations in underground mining processes at optimum deposit exploitation.

2 Methodology

The investigation of a research problem requires a certain methodology. Developing an optimization tool for technical processes makes the exact knowledge of KPIs as well as influencing factors necessary.

In a first step, each process of the conventional underground drilling and blasting cycle is analysed regarding relevance of research potential. In the second step, the most important Key Performance Indicators (KPIs) for the selected mining processes are identified. In a third step, the KPIs for blast design and roof support are examined regarding influencing parameters. In the next step, the structure of both optimizer concepts is set up, based on KPIs and influencing parameters. The methodology is shown in figure 1. The research results and developed concepts are presented in chapter 3.
3 Concept Development

3.1 Analysis of underground mining processes

The processes of the underground mining are:

- blast design (drilling, charging and blasting)
- ventilation
- loading & hauling
- roof support (scaling and bolting)
- surveying

The state of research in blast design optimization indicates several scientific approaches, patents and industrial software solutions. Underground blast design is less explored in terms of real-time optimization though and therefore in the focus of this work [Song et al. 2013]. Ventilation optimization with ventilation-on-demand systems is a well-developed research area and there are already several software solutions and implementation approaches on the market [Acuña et al. 2016, Babu et al. 2015, Cervinka et al. 2010]. This process step is therefore excluded from this study. According to Ahmed [2013], most of the energy within the underground drilling and blasting cycle is consumed for loading and hauling. The reduction of the energy consumption of underground mobile loading and hauling equipment is a constant task for equipment manufacturers and therefore not further addressed in this paper [Paraszczak et al. 2014]. Roof support has a smaller impact on the total energy consumption of the mine than the processes described beforehand but it remains crucial for HSE aspects. As the drilling process for bolt installation is similar to the drilling process for blast holes, synergies can be exploited. The roof support process has therefore been chosen for the development of a new optimization approach by the authors.

3.2 Identification of KPIs

After the process analysis, the most important Key Performance Indicators (KPIs) for the selected mining processes are identified. The most commonly used KPIs in underground mining operations are costs and energy use per tonne of value material or moved material [Ahmed 2013]. Costs are also expressed in operational expenditures (OPEX) and capital expenditures (CAPEX). Another relevant KPI for blast design processes is the consumption of explosives. Other important KPIs for the roof support process are roof movement per area and time sequence and accidents per time.

3.3 Documentation of influencing parameters

In a third step, the KPIs for blast design and roof support are examined regarding influencing parameters. Those are allocated as shown in Table 1.
### 4 Real-Time Data Concepts for Blast Design and Roof Support Process Optimization

Based on the KPIs and influencing parameters for the selected mining processes (Table 1), concepts for a Drilling & Blasting Optimizer and a Bolting Optimizer have been designed. The principles for both optimization approaches are outlined as follows.

#### 4.1 Drilling and Blasting

The Drilling & Blasting Optimizer concept combines the steps drilling, charging, blasting (fragmentation control) and drill pattern planning (Figure 1). While drilling a borehole, continuous data acquisition on rock parameters and geometry of the actual drill pattern is acquired. Enhanced measurement while drilling (MWD) technology is required for this. With the information of every new borehole, the actual pattern is updated in order to reach the ideal energy distribution for blasting. This leads to reduced drilling meters as well as a lower energy consumption. During the charging process, there is also room for adapting the explosive quantity with changing the filling factor or for changing the delay sequencing. After each blast, the grain size distribution is measured and compared to the plan. By applying sensors along the transport chain, grade control is possible which supports optimal downstream processes as well as a reaction on changing customer requirements. By documenting and evaluating a high number of blasts, a better understanding of the influencing parameters is achieved which will lead to better blasting results. With the control over costs and parameters of all mine-to-mill processes using adequate sensors technologies, the overall optimum fragmentation for blasting, loading, hauling, grinding and milling can be identified.
4.2 Bolting

The Bolting Optimizer works similar to the Drilling Optimizer, aiming for a certain borehole density, depending on the rock quality of the roof. It consists of the steps drilling, bolt installation and monitoring. Changes in the geology influence the drill pattern significantly. With the safety aspect as a driving force, permanent roof support monitoring is crucial. Each movement in the roof surface and forces to the bolts are detected and recorded. This serves as a holistic warning system for rockfalls or collapses and helps to improve roof bolting grid for future application.

5 Conclusion

The two optimizer concepts presented in this study aim to close the gap between existing technologies and to support efficient, safe underground mining processes. Mine operators could benefit especially from continuous updates of mine data. The presented drilling & blasting and bolting optimizer concepts are based on such updates and show - in case of the drilling & blasting concept - how energy distribution and drilling meter reduction could be achieved. The real-time data bolting optimizer concept supports the implementation of comprehensive monitoring of the mine and consequently increases mine safety significantly.
Based on the theoretical structure of the two optimizers, sensor technologies would have to be evaluated for the generation of reliable data. Also, enhanced MWD techniques play an important role in the drilling processes of the optimizers. Thus once sensors and data infrastructure have been established, the necessary software structure would have to be developed and tested. In the end, all operational mining processes should be more interconnected to achieve mine-to-mill optimization.

ACKNOWLEDGEMENTS

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Improved grade classification through sequential resource model updating using real time monitoring data in underground mining

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ABSTRACT:

A sequential resource model updating methodology, which involves prior resource estimation, stope development and data sampling, and sequential data assimilation to update the resource model, has been recently developed and successfully applied to mine production of a massive orebody (Si et al., 2017). This paper demonstrates the application of the methodology to a challenging dataset from a thin orebody, with an emphasis on examining the feasibility and efficiency of different resource updating methods. A solid vein model for the orebody Wihelm Stehender at the Reiche Zeche mine in Germany was first constructed. Four valuable minerals (galena, pyrite, sphalerite and arsenopyrite) were examined based on mineral statistics from sampled drillhole data. Centred log-ratio transformation was performed for mineral compositional contents to comply with the closure of compositional data and conditional Gaussian simulation and Block Kriging were then conducted to serve as ground truth grade values and prior estimates, respectively. Sequential mine production in the form of shrinkage stoping suitable for the narrow vein structure was then modelled. After each blast, mineral compositional contents at exposed hanging wall and bottom faces were sampled and used for real time data assimilation in the resource model. Four resource updating methods, including a classical geostatistical method (Ordinary Kriging) and three machine learning methods (support vector regression, random forest and radial basis function network) were used for the resource model update and their respective performance was compared in terms of accuracy and efficiency. The results have shown that all four methods can achieve significant improvement in grade estimation for planned resources. The Ordinary Kriging method can provide reasonably reliable estimates including their variance, but it becomes computationally expensive as collected datasets accumulate over time. The support vector regression method, which is the most computational efficient and also yields excellent performance, is recommended for resource model update when a large volume of sampling data is available.
Figure 1. Resource model update at Wilhelm Stehender orebody: (a) geological model, (b) solid vein model, (c) virtual asset model, and (d) real-time resource estimation.

REFERENCE:

Unraveling the Capability of Artificial Intelligence for Prediction of Rock Fragmentation

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ABSTRACT:
The fragment size distribution of blasted rock material is an imperative determinant of the economics associated with other mine operations. Obtaining optimized fragment size distribution from blasting is necessary for optimizing downstream processes like loading, hauling and processing. Empirical and mechanistic models have been used for iteratively arriving at optimum blast design parameters to improve rock fragmentation. Among the existing models, Kuz-Ram and modified Kuz-Ram have become the most popular in the mining industry. However, these models are subject to inconsistencies and produce results that are very often unsatisfactory. They are particularly known to perform poorly in predicting the fines and upper limit block sizes resulting from blasting. Hence, a more rigorous and accurate approach in modelling rock fragmentation is required. Artificial intelligent models offer a better approach for improving predictive performance in most real-world problems. In this study, we analyze and compare Feedforward Back Propagation Neural Network (BPNN) and Extreme Gradient Boosting Machine (XGBoost) against empirical models in modelling rock fragmentation, using data from two open-pit mines in Ghana. The findings based on five statistical measures proved that the XGBoost and BPNN can offer more accurate and credible estimation than the commonly used traditional methods. However, the XGBoost, compared to BPNN, revealed more accurate prediction capability. Artificial intelligence can be exploited as a powerful means for predicting and optimizing rock fragmentation in the mining industry.

Keywords: Artificial Intelligence, XGBoost, BPNN, Rock Fragmentation, Kuz-Ram model, Modified Kuz-Ram model, Blasting

1 Introduction
Blasting is the succeeding phase after drilling in the fragmentation process and is considered the second most important process after drilling. These two processes constitute the foundation of rock excavation in many mining operations, resulting in a desired muckpile profile and fragmentation size distribution. Rock fragmentation is regarded as one of the most substantial activities of the mine production cycle owing to its proportionate effects (cost) on subsequent operations such as loading, hauling and crushing. There is abundant evidence and consensus on the economics of drilling and blasting in the mining industry. According to Kazem and Bahareh (2006), drilling and blasting cost constitute up to 30% of the total operational costs in open-pit mines. This could increase up to 50% due to boulders and the requirement of secondary blasting. Mackenzie (1966, 1967) noted that the efficiency of all the subsystems is dependent on the fragmentation. He indicated that loading, hauling and crushing costs dwindled with increasing rock fragmentation, while drilling and blasting costs increased with increasing rock fragmentation. Poor fragmentation results in relatively lesser excavator productivities, wear and damages to crushers and excavators, reduced crusher throughput, and overall reduction in ounces produced.

Several factors influence rock fragmentation. Siddiqui et al., (2009) lists two main factors affecting the ultimate results of a blast. These factors are: Controllable and uncontrollable factors or variables. Kansake et al. (2016) and Enayatollahi (2013) give specific classification of the factors as geometrical (burden, spacing, hole depth and charge length), explosive (type, amount/quantity and properties) and rock factors (rock strength, porosity, specific gravity, discontinuity information and ground water condition). These factors form a necessary input into any rock fragmentation model.

Being able to predict the fragmentation of a rock mass by blasting offers substantial advantage in providing muck with a desirable size distribution and specifications for aggregate purposes or mill feed. Cognizant of this, various models have been developed over the years that predict the size distribution resulting from particular primary blast design (Cunningham, 2005; Cho and Kaneko, 2004). These techniques are broadly categorized into empirical and mechanistic models such as Bond-Ram model, Kou-Rustan equation, Energy Block Transition (EBT) model, Swedish Detonic Research Foundation (SveDeFO) model, Kuz-Ram model, Larson model, RosinRammler model, Kuznetsov–Cunningham–Ouchterlony (KCO) model, Chung and Katsabanis model, Modified Kuz-Ram model, Crushed Zone Model (CZM) and Two Component Model (TCM) (Rosin and Rammler, 1933; Kuznetsov, 1973; Cunningham, 1983; Lilly, 1986; Monjezi et al., 2012; Ouchterlony, 2005).

In addition, a number of studies have been conducted to improve blast design, considering the prediction of fragmentation after blasting (Ortuta and Drebenstedt 2012; Sontamino and Drebenstedt 2012). Although the Kuz-Ram model, which is purely empirical, is the most widely used fragmentation prediction model (Cunningham, 2005; Djordjevic, 1999; Kansake et al., 2016), it has been identified to be liable to several inconsistencies. In their comprehensive study of the existing empirical models, Kansake et al. (2016) noted that it underestimates the quantity of fines produced from a blast. Another drawback is that it does not consider accurate timing or delay offered by modern electronic detonators. It also assumes that the energy released by explosives in adjacent holes does not interfere with each other. Although the modified Kuz-Ram was introduced to address the above mentioned drawbacks, it has been pointed out in Kansake et al. (2016) to be liable to uncertainties. The process involved in the modification are detailed in Gheibie et al. (2009), Vamshidhar and Venkatesh (2010) and Kansake et al. (2016).
In recent years, researchers have investigated a variety of statistical and machine learning approaches to predict rock fragmentation (Aler et al., 1996; Mario and Francesco, 2006; Monjezi et al., 2012; Gheibie et al., 2009; Shi et al., 2012; Salimi et al., 2012; Badroddin et al., 2013; Bakhtavar et al., 2014; Enayatollahi et al., 2014). Based on literature covered pertaining to this study, the accuracy achieved by previous findings has not been satisfactory. In addition, most of the models did not consider all important factors affecting rock fragmentation, as stated earlier in this section. Moreover, the literature does not contain comparative studies on the predictive performance of artificial intelligence and empirical models. In view of the limitations or constraints in the current body of knowledge, more studies are required to identify more accurate and comprehensive models for predicting fragment size distribution resulting from blasting.

This study focuses on developing models based on Feedforward Back Propagation Neural Network (BPNN) and Extreme Gradient Boosting Machine (XGBoost) for predicting the fragment size distribution resulting from open-pit production blasting. BPNN (Hecht-Nielsen, 1989) offers an alternative that has the potential to establish a model from non-linear, complex and multidimensional data. Artificial neural network offers real benefits over traditional modelling, including the ability to handle large amounts of noisy data from dynamic and nonlinear systems without a priori information of the processes involved. BPNN provides an adequate solution even when the data are incomplete or ambiguous (Handhel, 2009). One of the interesting properties of BPNN is that it makes accurate predictions. This predictive ability is due to the degree of liberty that allows it to better capture the non-linearity of a system compared to other modelling techniques (Pan et al., 2013). XGBoost is a novel supervised learning artificial intelligent algorithm. This algorithm was chosen due to its noteworthy advantages including dealing with missing values in a dataset, implying a computationally efficient variant of gradient boosting algorithm (Friedman, 2001) and providing adequate results in machine learning competitions (Chen, 2014). It has been successfully used in other scientific applications (e.g. Möller et al., 2016; Tamayo et al., 2016).

The most important factor behind the success of XGBoost is its scalability in all scenarios. The system runs more than ten times faster than existing popular solutions on a single machine and scales to billions of examples in distributed or memory-limited settings. The scalability of XGBoost is due to several important systems and algorithmic optimizations. These innovations include: a novel tree learning algorithm for handling sparse data; a theoretically justified weighted quantile sketch procedure, enabling handling instance weights in approximate tree learning (Tianqi and Carlos, 2016). Using XGBoost, we expect to identify robust patterns in the dataset capable to predict the desired fragmentation. This study, to the best of our knowledge, is the first time the algorithm is being used to predict fragment size distribution from blasting. The main objective of this study is to test the predictive capability of BPNN and XGBoost against the traditional methods namely, Kuz-Ram and modified Kuz-Ram models. Finally, we used statistical indices such as the mean squared error (MSE), correlation coefficient ($R$), coefficient of determination ($R^2$), mean absolute error (MAE) and relative absolute error (RAE) to evaluate the accuracy and efficiency of the proposed models by comparing model outputs to field measured results of rock fragmentation.
2 Methodology

2.1 Study Area

Data for the study were obtained from two large scale gold mines in Ghana, Mine A and Mine B, both located in south-western Ghana. Mining operations in both mines are conducted by conventional open-pit method. Mine A is within the Tarkwaian group of rocks, with mineralisation confined to a 50 m thick section of the Banket conglomerate unit (Griffins et al., 2002). The mineralisation in Mine B is predominantly of the Birimian supergroup, which has minor granitic intrusions bounded by large granitoid bodies to the east and west (Johnson et al., 2012).

2.2 Data

2.2.1 Geometric and explosive data

In this study, data obtained consist of controllable and uncontrollable parameters, including geometric, explosive and rock parameters of both mines. Table 1 and Table 2 present the parameters (geometric and explosive) used in this study. These data were taken from blast design plans at both mines. The bulk explosive used at both Mines is Riomex 8,000 (20% Ammonium Nitrate Porous Prills, ANPP and 80% emulsion). The average density is 1.2 g/cm³ (1,200 kg/m³) and the average VOD is 4,900 m/s. The relative weight strength of Riomex 8,000 is 83%.

Tab. 1: Geometric Blast Parameters of Mines A and B

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mine A</th>
<th>Mine B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Blast 1</td>
<td>Blast 2</td>
</tr>
<tr>
<td>Spacing [m]</td>
<td>5.5</td>
<td>5.5</td>
</tr>
<tr>
<td>Burden [m]</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Bench height [m]</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Hole diameter [mm]</td>
<td>165</td>
<td>165</td>
</tr>
<tr>
<td>Ave. hole depth [m]</td>
<td>7</td>
<td>6.64</td>
</tr>
<tr>
<td>Ave. sub-drill [m]</td>
<td>1</td>
<td>0.64</td>
</tr>
<tr>
<td>Ave. final stemming height [m]</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

Tab. 2: Explosive Parameters of Mines A and B

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mine A</th>
<th>Mine B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Blast 1</td>
<td>Blast 2</td>
</tr>
<tr>
<td>Average quantity per hole [kg]</td>
<td>103</td>
<td>93.4</td>
</tr>
<tr>
<td>Volume blasted per hole [bcm]</td>
<td>165</td>
<td>165</td>
</tr>
<tr>
<td>Powder factor [kg/m³]</td>
<td>0.62</td>
<td>0.57</td>
</tr>
<tr>
<td>Loading density [kg/m]</td>
<td>25.7</td>
<td>25.7</td>
</tr>
<tr>
<td>Average Charge length [m]</td>
<td>4</td>
<td>3.64</td>
</tr>
</tbody>
</table>
2.2.2 Rock data

The rock parameters were determined using laboratory tests conducted in the geotechnical laboratory of the University of Mines and Technology (UMaT). Uniaxial compressive strength (UCS) and bulk density tests were conducted on rock samples from Mine A. Twelve cubic samples of dimensions 50mm × 50 mm × 50 mm were used for the UCS tests, while 24 irregular samples were used for the bulk density tests. Geotechnical cell mapping was also conducted at Mine A to determine joint information and general rock description. Rock characteristics data for Mine B were obtained from the geotechnical department of the mine. Summary of the rock data for Mines A and B are shown in Table 3. In this study, three blasts were studied from Mine A, while four blasts were considered in Mine B.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mine A</th>
<th>Mine B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uniaxial Compressive Strength [MPa]</td>
<td>43.6</td>
<td>41.8</td>
</tr>
<tr>
<td>Bulk density [tonnes/m³]</td>
<td>2.39</td>
<td>2.8</td>
</tr>
<tr>
<td>Joint spacing [m]</td>
<td>1.56</td>
<td>2.5</td>
</tr>
</tbody>
</table>

2.3 Fragmentation Analysis in Split-Desktop 3.1

Images of blasted muckpiles were sampled for fragmentation analysis. They were obtained using a digital camera with very high image quality. Location of the images within the muckpiles was carefully chosen to ensure that they were representative of the muckpile. Two metallic poles of length 1.5 m were used as scaling objects in each image. The images of the muckpiles obtained were analyzed using Split-Desktop 3.1 software and the results used as the basis for the model comparison. Five images were analyzed and superimposed on each other to represent the fragment size distribution from each blast. The image analysis procedure in Split-Desktop 3.1 software is summarized in Figure 1. A sample output from SplitDesktop is shown in Figure 2. The summary statistics of the input and output parameters are shown in Table 4.

![Image Acquisition](image1)
![Scale Setting](image2)
![Auto Delineation](image3)
![Manual Delineation](image4)

Fig. 1: Image Analysis Procedure in Split-Desktop 3.1
Fig. 2 Fragment size distribution generated from image analysis in Split-Desktop 3.1

Tab. 4: Summary statistics of the input and output parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Mean</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hole depth [m]</td>
<td>6.9</td>
<td>7.06</td>
<td>7.2</td>
</tr>
<tr>
<td>Hole diameter [mm]</td>
<td>115</td>
<td>125</td>
<td>165</td>
</tr>
<tr>
<td>Burden [m]</td>
<td>2.9</td>
<td>3.36</td>
<td>5</td>
</tr>
<tr>
<td>Spacing [m]</td>
<td>3.2</td>
<td>3.78</td>
<td>5.5</td>
</tr>
<tr>
<td>Bench height [m]</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Subdrill [m]</td>
<td>0.8</td>
<td>0.98</td>
<td>1.2</td>
</tr>
<tr>
<td>Drilling deviation [m]</td>
<td>0.1</td>
<td>0.26</td>
<td>0.4</td>
</tr>
<tr>
<td>Drilling precision [m]</td>
<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>Powder factor [kg/m³]</td>
<td>0.61</td>
<td>0.9</td>
<td>1.16</td>
</tr>
<tr>
<td>Rockmass description (RMD)</td>
<td>90</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>Joint plane spacing (JPS)</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Joint plane angle (JPA)</td>
<td>40</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>Rock density influence (RDI)</td>
<td>9.75</td>
<td>18</td>
<td>20</td>
</tr>
<tr>
<td>Hardness Factor (HF)</td>
<td>8.36</td>
<td>8.43</td>
<td>8.71</td>
</tr>
<tr>
<td>Blastability Index (BI)</td>
<td>99.2</td>
<td>103</td>
<td>104</td>
</tr>
<tr>
<td>Charge length [m]</td>
<td>3</td>
<td>3.86</td>
<td>4.2</td>
</tr>
<tr>
<td>Stemming height [m]</td>
<td>3</td>
<td>3.2</td>
<td>4</td>
</tr>
<tr>
<td>Amount of explosives per hole [kg]</td>
<td>49.9</td>
<td>60.9</td>
<td>100</td>
</tr>
<tr>
<td>Young’s modulus [GPa]</td>
<td>60</td>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>Delay (RIONEL DDX 25/500) [m/s]</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>Velocity of Detonation (VOD) [m/s]</td>
<td>4900</td>
<td>4900</td>
<td>4900</td>
</tr>
<tr>
<td>Size [cm]</td>
<td>0</td>
<td>32.7</td>
<td>350</td>
</tr>
<tr>
<td>Fragmentation [×100%]</td>
<td>0</td>
<td>0.33</td>
<td>1</td>
</tr>
</tbody>
</table>

A total of 126 datasets were used for the artificial intelligence modelling. The study used 90 of the datasets for model training, 18 for model validation, while the remaining 18 were used as the test set.
3 Fragmentation Modelling

3.1 **Kuz-Ram Model**

In the 1973, Kuznetsov demonstrated a procedure to obtain rock fragmentation. According to Kuznetsov, the mean fragment size and the powder factor of TNT, as well as geological structure, are the most important parameters. He also pointed out the relationship between average fragment size and the amount of explosive used in a particular rock type. The model comprises three fundamental equations: Kuznetsov’s equation (equation 1), Rosin-Rammler equation (equation 2) and uniformity equation (equation 3). The equations are summarized by Kuznetsov (1973) and Cunningham (1983).

\[ X_m = AK^{-0.8}Q^{1/6}R^{19/20} \]  

Here, \( X_m \) is the mean particle size, cm; \( A \) is rock factor (usually between 0.8 and 22 depending on the nature of the rock); \( K \) is the powder factor, kg/m\(^3\); \( Q \) is the quantity of explosives per hole, kg; \( RWS \) is the relative weight strength of the explosive used (RWS of ANFO = 100); and 115 is the relative weight strength of TNT. The Rosin-Rammler equation (equation 2) was introduced to predict the distribution resulting from the blast.

\[ R_x = \exp \left[ -0.693 \left( \frac{X}{X_m} \right)^n \right] \]  

Where \( R_x \) is the mass fraction retained on screen opening \( X \) and \( n \) is the uniformity index usually between 0.7 and 2 based on the blast geometry. The uniformity index, \( n \), is found using equation 3. It is a function of blast geometric parameters.

\[ n = \left( 2.2 - \frac{14B}{d} \right) \sqrt{\left( \frac{1+S/B}{2} \right) \left( 1 - \frac{W}{B} \right) \left( \frac{BCL-CCL}{L} \right)} + 0.1 \left( \frac{L}{H} \right)^{0.1} \]  

Where \( B \) is burden, m; \( S \) is spacing, m; \( d \) is the hole diameter, mm; \( W \) is the standard deviation of drilling precision, m; \( L \) is the charge length, m; \( BCL \) is the bottom charge length, m; \( CCL \) is the column charge length, m; and \( H \) is the bench height, m.

3.2 **Modified Kuz-Ram Model**

In this model, there is a modification of the Kuznetsov equation and the uniformity index. Here, a factor of 0.073 is introduced to Kuznetsov’s equation and the rock factor is replaced by the blastability index (BI). In addition, the Rosin-Rammler function is maintained as in the original Kuz-Ram model. The modified Kuznetsov equation is given in equation 4.

\[ X_m = 0.0736BI \left( \frac{V_o}{Q_e} \right)^{0.8} Q_e^{1/6} \left( \frac{S_{ANFO}}{115} \right)^{-19/30} \]  

In the above equation, \( BI \) is the blastability index; \( V_o \) is the volume of material blasted per hole, m\(^3\); \( Q_e \) is the quantity of explosives per hole, kg. The modification of the Cunningham’s uniformity in-
dex is defined in equation 5 and used to characterise the fragmentation distribution (Kansake et al., 2016).

\[ n' = 1.88 \times n \times BI^{-0.12} \]

Where \( n' \) is the modified uniformity index; \( BI \) and \( n \) are defined in equations 4 and 3 respectively.

### 3.3 Feedforward Back Propagation Neural Network

The backpropagation artificial neural network (BPNN) is one of the most widely used artificial neural network (ANN) for engineering applications (Konaté et al., 2013; Haykin, 2007). The BPNN represented in Fig. 3 comprises three layers; input, hidden and output layers of processing units, with each layer feeding input to the next layer in a feedforward manner through a set of connections weights (Ziggah, 2016).

The input layer receives the input data and the output layer presents the final results of the computation. Between these two layers is the hidden layer containing hidden neurons where intermediate computations are performed based on data transferred from the input layer. The efficiency of the BPNN model is influenced by the number of hidden neurons, hidden layers, type of activation functions, weights and biases applied. Generally, determination of the number of hidden neurons is via sequential trial and error procedure. This is because universally, there has not been a convergence on the exact number of hidden neurons needed to approximate a given function. In this study, the optimum number of hidden neurons was obtained based on the lowest error measure as presented in Table 6.

![Fig. 3: Schematic representation of BPNN](image)

With respect to the optimum number of hidden layers in the network, we adapted the approach given by Hornik et al. (1989), where it was shown that the BPNN with one hidden layer is sufficient as a universal approximator of any discrete and continuous functions. Cognizant of this, one hidden layer was used in this study. Also, the hyperbolic tangent activation function was chosen for the hidden layer to introduce non-linearity to the network, while a linear transfer function was selected for the output node. According to Yonaba et al. (2010), the hyperbolic tangent function is defined in Eq. 6 as
\[ f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1 \]

Where \( x \) is the sum of the weighted inputs. The training of BPNN algorithm can be described as a non-linear optimization problem. In Konaté et al. (2015), \( w^* \) is presented in Eq. 7 as

\[ w^* = \text{argmin} \ E(w) \]

Where \( w \) is the weight matrix and \( E(w) \) is the error function. The objective of training a network is to find the optimum weight connection \( (w^*) \) that minimizes \( E(w) \) such that the estimated outputs from the network will be in conformity with the output data. This \( E(w) \) is estimated at any point of \( w \) as given in equation 8.

\[ E(w) = \sum_n E_n(w) \]

Where, \( n \) is the number of training examples and \( E_n(w) \) is the output error for each example, \( n \). According to Konaté et al. (2015), \( E_n(\omega) \) is estimated using equation 9.

\[ E_n(\omega) = \frac{1}{2} \sum_j (d_{nj} - g_{nj}(\omega))^2 \]

Where \( d_{nj} \) and \( g_{nj} \) are the network outputs and computed values of the \( j \)th output neuron for the \( n \)th example, respectively. The objective function to be minimized is obtained by substituting equation 9 into equation 8 (Konaté et al., 2015) and presented as equation 10.

\[ E(w) = \frac{1}{2} \sum_n \sum_j (d_{nj} - y_{nj}(w))^2 \]

The training process continues by adjusting the weight of the output neurons and then proceeds towards the input data until the error function reaches an acceptable value. Numerical optimization algorithms to implement this weight adaptation can be found in Nocedal and Wright (2006). The Levenberg-Marquardt Algorithm (LMA) was chosen as the training function. This is because it reaches convergence faster and is more efficient compared to others such as gradient descent algorithm, Scaled Conjugate Gradient and Fletcher-Powell Conjugate Gradient. This was corroborated by the works of Wang (2009), Ziggah (2016) and Hagan and Menhaj (1994). Prior to training the algorithm, the input and output data were normalized in the interval [-1, 1] following the approach proposed by Mueller and Hemond (2013). This increases convergence speed and reduces the chances of getting stuck at local minima (Ziggah, 2016).

### 3.4 Extreme Gradient Boosting Machine

Extreme Gradient Boosting Machine (XGBoost) (Chen and Guestrin, 2016) is a supervised machine learning algorithm, which is an improved algorithm based on the gradient boosting decision tree. It can construct boosted trees efficiently and operate in parallel. The core of XGBoost is to optimize the value of a defined objective function that includes a regularization term, used to reduce the chances of overfitting, as well as support for arbitrary differentiable loss functions. In this study, we developed and trained an XGBoost regressor to predict rock fragmentation. The XGBoost models an objective function, \( \text{Obj} \) (equation 11) which is defined in two parts, a loss function over the
training set, as well as a regularization term which penalizes the complexity of the model (Chen and Guestrin, 2016).

\[
\text{Obj} = \sum_i L(y_i, \hat{y}_i) + \sum_k \Omega(f_k)
\]

Where \(L(y_i, \hat{y}_i)\) is the loss function, \(y_i\) is the target and \(\hat{y}_i\) is the prediction. In this study, the loss function used for the XGBoost regressor is the mean squared error. Details about the types of loss functions can be found in Chen and Guestrin (2016). \(\Omega(f_k)\) is the regularization term, which controls the complexity of the tree \(f_k\) and also reduces the chances of overfitting, defined in the XGBoost model (Chen and Guestrin, 2016) as equation 12.

\[
\Omega(f_k) = \gamma T + \frac{1}{2} \lambda w^2
\]

\(T\) is the number of leaves of tree \(f_k\), and \(w\) is the leaf weights, which is the predicted values stored at the leaf nodes. The \(\gamma\) and \(\lambda\) are configurable parameters. \(\gamma T\) provides a constant penalty for each additional tree leaf and \(\lambda w^2\) penalises extreme weights. The XGBoost algorithm performs computations in an iterative procedure. The objective function for any current iteration \(m\) in terms of the prediction of the previous iteration \(\hat{y}_i^{(m-1)}\), adjusted by the newest tree \(f_k\) is defined in Eq. 13 as

\[
\text{Obj}^m = \sum_i L(y_i, \hat{y}_i^{(m-1)} + f_k(x_i)) + \sum_k \Omega(f_k)
\]

The algorithm can then be optimized to find the \(f_k\) which minimizes the objective function in equation 13. The Second-order approximation can be used to quickly optimize the objective function in the general setting (Friedman, 2000) defined in Eq. 14 as

\[
\text{Obj}^m \approx \sum_i \left[ L(y_i, \hat{y}_i^{(m-1)} + g_i f_k(x) + \frac{1}{2} h_i f_k(x)^2 \right] + \sum_k \Omega(f_k) + \text{constant}
\]

Here, \(g_i\) and \(h_i\) are the first and second order derivatives, respectively, of the loss function for instance \(i\) (Chen and Guestrin, 2016), where

\[
g_i = \frac{dL(y_i, \hat{y}_i^{(m-1)})}{d\hat{y}_i^{(m-1)}} \quad \text{and} \quad h_i = \frac{d^2L(y_i, \hat{y}_i^{(m-1)})}{d(\hat{y}_i^{(m-1)})^2}
\]

With the constant terms removed, the objective function (Chen and Guestrin, 2016) is simplified in equation 15 as

\[
\text{Obj}^m = \sum_i [g_i f_k(x) + \frac{1}{2} h_i f_k(x)^2] + \sum_k \Omega(f_k)
\]

The XGBoost modelling was carried out in R programming environment. The modelling of XGBoost requires series of parameters which need to be configured as stated in equation 12. These parameters are presented in Table 5. The parameters (Chen et al., 2018) were optimized by grid search and the whole process for an accurate XGBoost model automated. This approach prevents human interference and possible discrepancies, which may arise in the process of using trial and error technique.
### Tab. 5: The XGBoost regressor parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of boosting round (iterations)</td>
<td>c(100,200)</td>
</tr>
<tr>
<td>maximum depth</td>
<td>c(10, 15, 20, 25)</td>
</tr>
<tr>
<td>Subsample ratio of columns</td>
<td>seq(0.5, 0.9, length.out = 5)</td>
</tr>
<tr>
<td>Gamma</td>
<td>c(0.0, 0.2, 1)</td>
</tr>
<tr>
<td>Eta</td>
<td>c(0.01,0.3, 1)</td>
</tr>
<tr>
<td>Minimum child weight</td>
<td>seq(1,10)</td>
</tr>
<tr>
<td>subsample</td>
<td>1(default)</td>
</tr>
<tr>
<td>Objective function</td>
<td>Linear</td>
</tr>
</tbody>
</table>

### 3.5 Evaluation Metrics

The BPNN and XGBoost models’ performance for training, validation and testing data was evaluated using various statistical measures by comparing their output at various stages (training, validation and testing) to measured data. In this study, the coefficient of determination ($R^2$), correlation coefficient ($R$) and mean squared error (MSE) were used as statistical indicators to determine the optimum BPNN structure and the best XGBoost model. For comprehensive model performance evaluation in relation to the training, validation and testing results, the relative absolute error (RAE) and mean absolute error (MAE) were implemented in this study. The same evaluation metrics were utilised for the empirical models. The mathematical expression of the evaluation metrics are given in Krause et al. (2005) and Ali and Abustan (2014).

### 4 Model Application

The proposed BPNN model obtained for predicting rock fragmentation size distribution consists of three layers: input layer, hidden layer and output layer. With regard to the models, the data was divided into training, validation and testing sets, as described in section 2. It should be noted that the same dataset was used for both models. The BPNN network used consists of 22 input parameters, a hyperbolic tangent function transforms the input to a single hidden layer, and a linear transfer function to the output layer. Using the LMA, the network was trained for 1,000 epochs. After training several networks, the best BPNN model based on the lowest MSE and largest $R$ and $R^2$ (as shown in Table 6) was [22-5-1]. Thus, for predicted fragmentation (output vector), there were twenty two inputs, with five hidden neurons. The regression analysis of the BPNN model is presented in Fig. 4.

For the XGBoost model, the parameters for the algorithm were optimized by grid search and the process automated for each training step. To prevent overfitting, column sub-sampling was introduced. Interestingly, we observed a high computation speed during the process which is consistent with the study reported by Chen and Guestrin (2016). The final parameters obtained are presented in Table 5, based on the lowest MSE, and largest $R$ and $R^2$ shown in Table 6. Figure 5 presents the regression analysis of the model. It is imperative to note that the MSE (Table 6) utilised in this study was performing as the optimality measure to assist in selecting the most adequate XGBoost and BPNN models for predicting rock fragmentation. On the basis of the results, the MSE value (Table
obtained for the training data in both models show the closeness of the fitted models to the training data. Figs. 4 and 5 describe the closeness of the XGBoost and BPNN predictions to the measured fragmentation based on the training, validation and testing dataset.

Tab. 6: The results from the training, validation and testing dataset for the models developed

<table>
<thead>
<tr>
<th>Dataset</th>
<th>BPNN</th>
<th>XGBoost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSE</td>
<td>5.35E-04</td>
<td>1.64E-05</td>
</tr>
<tr>
<td>R</td>
<td>0.998</td>
<td>0.999</td>
</tr>
<tr>
<td>R²</td>
<td>0.996</td>
<td>0.999</td>
</tr>
<tr>
<td>Validation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSE</td>
<td>5.21E-03</td>
<td>4.95E-03</td>
</tr>
<tr>
<td>R</td>
<td>0.997</td>
<td>0.981</td>
</tr>
<tr>
<td>R²</td>
<td>0.994</td>
<td>0.963</td>
</tr>
<tr>
<td>Testing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSE</td>
<td>9.46E-04</td>
<td>6.23E-06</td>
</tr>
<tr>
<td>R</td>
<td>0.997</td>
<td>0.999</td>
</tr>
<tr>
<td>R²</td>
<td>0.995</td>
<td>0.999</td>
</tr>
</tbody>
</table>

Moreover, the high $R^2$ and $R$ values (Table 6) obtained in training further established the quality of training performances in both models. Here, the $R^2$ values attained for the training data indicate the tolerance of the models. Thus, approximately 99% changes in the measured training target values are explained by the variation in output values during the training stage. The $R$ results, on the other hand, prove the strength and direction of linear dependency existing between the training targets and training outputs. This is also evident in Figs. 5 and 6. The MSE, $R^2$ and $R$ values at the training stage also suggest that the tuning capability of the models are adequate for the specified training data. Drawing on the outcomes in Table 6, it can be concluded that both models attained acceptable training performance based on the MSE values. Hence, it is demonstrated that in the case of this study, the XGBoost and BPNN have both proved greater learning abilities. In Table 6, it is also evident that the XGBoost model showed superiority in performance with regards to the training, validation and testing datasets, due to the lowest MSE, and largest $R$ and $R^2$ compared to the BPNN model. Nevertheless, the MSE of the models in the validation stage are in close agreement with the MSE from the training stage. The high values of $R^2$ and $R$ attained with regards to the training data suggest that our models did not compromise to overfitting. In Table 6, the performance of the XGBoost model on the testing dataset is proven by the lowest MSE compared to the BPNN, although both models attained high $R^2$ and $R$ values. This can also be inferred from Figs. 4 and 5.

The empirical models, Kuz-Ram and modified Kuz-Ram were only applied on the testing data points. Thus, the same testing datasets used for the BPNN and XGBoost modelling were applied for the empirical models to ensure a more consistent analysis. The modified Kuz-Ram model had the lowest MSE and also the largest correlation coefficient, $R$. Although the results suggest tolerance with regard to predicting rock fragmentation, the superiority of the modified Kuz-Ram model to the Kuz-Ram is evident when their error measures are compared. The results obtained here also confirm the claim noted in Kansake et al. (2016), that the modified Kuz-Ram model is efficient and can
provide better blasting fragmentation results than the kuz-Ram model. Fig. 6 and Table 7 show the regression analysis and results of the empirical models.

![Graph](image_url)

Fig. 4: Regression analysis of A) Training B) Validation and C) Testing for the BPNN model

<table>
<thead>
<tr>
<th>Testing Dataset</th>
<th>Kuz-Ram</th>
<th>Modified Kuz-Ram</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>4.408E-03</td>
<td>6.311E-04</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.990</td>
<td>0.987</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.982</td>
<td>0.975</td>
</tr>
</tbody>
</table>

![Graph](image_url)

Fig. 5: Regression analysis of A) Training B) Validation and C) Testing for the XGBoost model
Fig. 6: Regression analysis of A) Kuz-Ram B) Modified Kuz-Ram on the testing dataset

5 Results and Discussions

5.1 Model Performance

For a more objective assessment of the models, the MAE and RAE as stated in section 2.5 were applied. The choice of these dimensioned error statistics was based on the conclusions in Fox (1981) that these indices are able to quantify model performance in terms of prediction accuracy, thus informing the modeler and the reader about the actual size of the error produced by the model. The closer the MAE and RAE are to zero, the better the model prediction abilities. Table 8 presents the statistical results of XGBoost and BPNN models. The statistical results from the empirical models are also presented in Table 9.

Tab. 8: BPNN and XGBoost models performance assessment

<table>
<thead>
<tr>
<th>Error Measure</th>
<th>BPNN</th>
<th>XGBoost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAE</td>
<td>0.0155</td>
<td>0.0027</td>
</tr>
<tr>
<td>RAE</td>
<td>0.0489</td>
<td>0.0085</td>
</tr>
<tr>
<td>Validation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAE</td>
<td>0.0663</td>
<td>0.0356</td>
</tr>
<tr>
<td>RAE</td>
<td>0.2222</td>
<td>0.1193</td>
</tr>
<tr>
<td>Testing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAE</td>
<td>0.0206</td>
<td>0.0017</td>
</tr>
<tr>
<td>RAE</td>
<td>0.0671</td>
<td>0.0057</td>
</tr>
</tbody>
</table>

Tab. 9: Empirical models performance assessment

<table>
<thead>
<tr>
<th>Error Measure</th>
<th>Kuz-Ram</th>
<th>Modified Kuz-Ram</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>0.0511</td>
<td>0.0595</td>
</tr>
<tr>
<td>RAE</td>
<td>0.1663</td>
<td>0.1936</td>
</tr>
</tbody>
</table>
The MAE (Tables 8 and 9), were used to identify the variation in error by providing an inference on how close both empirical and artificial intelligence models predictions are to the measured fragmentation. From Table 8, it is proven that the XGBoost model predicted output is more accurate than the BPNN, although both models have acceptable performance and less liable to errors. Commenting on the empirical models, it is interesting to note that in Table 7, the MSE of the modified Kuz-Ram is the lowest. However, when the mean and relative values of their errors are computed, the Kuz-Ram model showed promising results compared to the modified Kuz-Ram. This confirms the importance of the claim made by Fox (1981). Consequently, the performances with respect to computing errors were found to be satisfactory.

5.2 Comparison of Models

In this study, artificial intelligent models (XGBoost and BPNN) were developed using 126 datasets; 90 for training, and 18 each for validation and testing of the models. The input parameters utilised in the study are summarised in Table 4. When the training and validation phase was completed, the testing phase was carried out. This was necessary to independently test and confirm the predictive power of the optimized models. The models applied on the test data provided a realistic estimate of their performance on the unseen data. The test results from the BPNN is compared to the measured data and the results from the empirical models. These are presented in Figs. 7 and 8. Graphical representation between the measured and the predicted fragmentation from BPNN shows some deviation, which also corroborates the results in Fig. 4 (c). However, the deviation from the measured fragmentation is greater in the empirical models as can be visualized from the Fig. 8.

In addition, it can be inferred from the figures that when the empirical models are compared to the BPNN, the BPNN depicts a more accurate prediction ability that the empirical models, as there is much deviation from the measured fragmentation.

![Graph](image)
The XGBoost model by virtue of the testing data and the error measure presented in Tables 6 and 8, depicted strong prediction abilities to the measured fragmentation. Due to the closeness of the respective predicted outputs from the XGBoost model, it is seen in Fig. 9 that the disparity between predicted and the measured fragmentation is very minimal. In Figs. 9 and 10, the XGBoost model results are compared to the measured and the results from the empirical models. The graphical representation also explains the superiority of the XGBoost model to the empirical models.
In addition, for a more objective comparison of the models, a graphical representation of their results is presented Fig. 11. From Fig. 11, it is ostensible that the XGBoost demonstrates much superiority in terms of the prediction ability when the total results are compared. The results here also confirm the lowest error measure produced by the XGBoost model during the formulation of the models.

6 Summary and Conclusions

Prediction of rock fragmentation has been common practice in the mining industry. This procedure is predominantly carried out using empirical models. Over the years, researchers have come up with improved ways to estimate fragmentation, but the accuracy of such models has become a major concern.

In this study, effort was made to develop artificial intelligent models (XGBoost and BPNN), and compare their performance to commonly used models. XGBoost and BPNN models, based on the supervised learning procedures, as well as the Kuz-Ram and modified Kuz-Ram models have been
studied. The findings revealed that the BPNN and XGBoost offered satisfactory prediction of rock fragmentation size distribution. However, the XGBoost compared to BPNN and empirical models, showed superior, fast, robust and more accurate prediction results. On the basis of the analysis, it has been demonstrated that combining both controllable and uncontrollable blasting parameters could produce accurate estimates of rock fragmentation. It is important to note that, although the present study has yielded improved models, the findings in this study cannot be extrapolated to every mine. Thus, the model should be modified to adapt prevailing parameters or conditions.

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Uncertainty Integration in Dynamic Mining Reserves

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ABSTRACT:

Mining resources are usually evaluated in a block model in which the mining area is discretized. In a few mining routines the uncertainty assessment at the local blocks is evaluated through geostatistical stochastic simulation methods, which allow the characterization of local probability distributions functions (pdfs), on point or block support, and, consequently the spatial uncertainty of grades per ore type. After the characterization of mean grades and uncertainty per block, the main role of mine planning consists on characterizing the time scheduling of reserves in terms of a mining sequence. The problem consists on transforming of the estimated grades and uncertainty of blocks in temporal flow of mean grades and consequent temporal uncertainty. The most straightforward approach consists on calculating the mining sequence to each of simulated realizations of blocks and calculate, afterwards, the uncertainty of each period. However, this approach needs to retain the N simulated models and calculate the mining sequence to each one of them, which can be a cumbersome task, particularly if the dimension of the block model is high. This work proposes one method to convert static into dynamic uncertainty of reserves by using a Gaussian Mixture Model. For each set of simulated values of one given block, just the local mean and variance are retained. Then, a Gaussian Mixture Model is applied to characterize the uncertainty of any period of the time schedule of the mine planning. Once the uncertainty of grades of a given period of the time scheduling is known, it can be used as an optimization parameter either in the context of internal blending strategy or in a selective mining method. This method is being implemented in Neves Corvo mine in order to be integrated in the mine routine, particularly in the short term mine planning. Results of this implementation will be presented.
You can´t improve what you can´t see
– The Talpasolutions´ approach to utilize real time machine data,
seeking enhanced mine productivity and efficiency

Mirko Liebetrau, Alexey Shalashinski, Michael Suciu
talpasolutions GmbH / Essen / Germany

ABSTRACT:

Mining companies today have recognized that emerging digital technologies, such as Internet of Things (IoT), Artificial Intelligence (AI) and machine learning will inevitably change the way of industrial mining. Faster and better decisions based on more transparent and rapidly available information will most certainly be a game changer for managing mining operations.

Far thinking mining executives already have recognized that the initial digitalization of equipment and processes leads the way to a safe, stable and automated production environment. In the initial phase of digitalization, utilizing automated real-time data streams from machines combined with big data technologies and algorithms will enable location tracking, activity monitoring, and machine health information. Mines and operations will become transparent, as well, without the necessity to allocate physical resources other than some hardware updates. Real-time data combined with historical and contextual data will allow to recognize patterns. Deep learning algorithms will continue to utilize such data-sets to provide operational insights and to enable predictions, as precise as no one can imagine today.

Gathering correct, reliable, traceable data in real-time is essential to efficiently control machines and processes. Industrial rugged sensors are needed to measure and monitor internal asset conditions. While GPS and tags based on radar or radio frequency are state of the art for machines, equipment and staff allocation, relevant contextual data can provide valuable information as well. Starting from precipitation, all available data on for example road conditions, petrographic details (hardness, density etc.), proximity to other equipment and personnel, will give insights on correlations, which cannot be identified without such advanced technology.

Gathering data is only one side of the medal. Transmitting data from the level of an individual machine up to multi-connected equipment is a further critical necessity to provide digital solutions to the industry. A major aspect therefore lies in the connectivity from machines and other data-sources to the analytical platform. In an underground environment wireless data transmission can be challenging because of the geology, mine layout, metal
However, 4G/5G radio frequency or extensive WiFi-coverage are already able to solve this challenge. In open pit mining LTE and satellite connectivity are state of the art.

As operational insights do not focus exclusively on real-time data but on previous findings and experiences, it is necessary to include historical and contextual data. Therefore, such data needs to be uploaded manually or automated via web-based interfaces in an appropriate software format. The actual data processing only starts with the automatic recognition of data types and formats, their temporal and spatial allocation to machines and processes. In a further step the analysis of the data processed in this way and the acquisition of valuable operational insights consists of transferring and combining the processed data to the complex processes of mining – and last but not least to the typical success indicators for mine productivity and efficiency.

1 Mine Digitization - a consequent approach to establish the next step of industrialization

Digitization, digitalization and digital transformation have long been a driver of sweeping change in the world around us – not only in our private life but also in our professional life.

Within the mining industry, digitalization will be a force that changes how employees interact, how machines interact, how the companies interact with entities such as government, authorities, communities, NGOs on one side, and on the other side with environmental and climate conditions, cultural and social factors etc. In effect, the whole nature of behavior and of the business is about to change\(^2\),\(^3\).

The foundation for this change is to be seen in the steadily evolving digital technologies and capabilities, means the IT- and communication technology. On the other side there is an ever-increasing amount of data generated daily on each mining site, still waiting to be properly captured, analyzed, and utilized.

Data are generated throughout a mine's lifecycle, from design through exploitation and processing to decommissioning and rehabilitation. The vast majority comes from the sensors embedded in the control systems of mining machinery and equipment. They are generated during the operating and maintenance phases as well as from deposit investigations and plans, engineering drawings, and various software systems. Unfortunately, these vast amounts and diverse formats of data are currently neither systematically recorded and stored nor comprehensively analyzed. Rather, the data seeps away via various stakeholders and data silos and is thus lost over the life cycle of the machines.

In the past, mining companies have typically made substantial investments in operational technologies to gather data from their operations, measuring and monitoring things such as vehicle move-

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\(^2\) Inmarsat Enterprise, 2017. The Future of IoT in Enterprise.

ment, weather and road conditions, operating hours, tonnages etc. and storing all kind of actual and historical data.

However, such systems typically operate in isolation and are only visible in the mining control center or on premise itself. It requires a substantial experience to make sense of the many screens, all with their own unique displays and user-interfaces.

In the future, this already enormous amount of data will increase exponentially as the industry continues to its journey of digital transformation. Additionally, the use of drones, SCADA systems, wireless sensors, 3D and radar scanning, automation and other technologies will increase exponentially, generating masses of data. A single hydraulic excavator currently produces over 250 MB of binary machine data per day.

Companies in the mining industry will not only benefit but also invest in new technologies. According to Accenture’s recently published research⁴, 82% of mining executives expect to invest in digital technology over the next 3 years. Further to this research, mining companies are applying digital technologies across their organization and across the whole production and value chain. This is in particular necessary and relevant for the companies to improve the profitability.

1.1 The challenge

Mining processes are complex and mining equipment – mobile, semi-mobile or stationary - is known to be capital-intensive. In underground mining standard load-haul-dump (LHD) vehicles are approximately 70% more expensive than wheel-loaders and/or trucks with the same capacity used in surface operations. In large opencast mines, huge off-high way trucks and heavy excavators and dozers represent a tremendous amount of investment of several hundreds of million USD.

The management of mines with large vehicle fleets are facing mine operators with further major challenges: skilled and experienced labor force is more and more difficult to find as mining is exposed to rough and hazardous working conditions and/or are lying in remote areas.

The mining industry therefore targets reducing risk exposure and increasing efficiency and productivity through the whole mining process and over all types of machinery. The industry follows various initiatives like autonomous operations and robotics, smart sensors, implementation of IIoT (Industrial Internet of Things) measures and tools. To name a few: Rio Tinto established “The mine of the future” in 2008 implementing intelligent tools and a remote operations center for autonomous operations⁵; Anglo American introduced autonomous drills in underground mining⁶. Original Equipment Manufacturers (OEM) like Caterpillar and Komatsu or Sandvik and Epiroc developed data driven and connected devices including smart sensors to generate and utilize data. Last but not least, new tech players offer IIoT solutions providing advanced and predictive analytics. Still, a comprehensive, independent and universally applicable solution is missing.

talpasolutions, a German based company, founded in 2016 as a spin-off of RWTH Aachen University, has noticed that quite a substantial portion of equipment of several OEM’s are already equipped with a broad variety of digital sensors, allowing to source deep insights, if the data would be transmitted and analyzed. Usually, the readings from only about 5% of the sensors are taken into consideration when monitoring the state of the machines. Even less information is currently used to predict the need for maintenance and repair. Being asked about the reason for this, most of the OEM’s representatives have pointed out that the absence of a solid system for data collection, structuring and analysis prevented making further use of such data.

1.2 talpasolutions´ approach

talpasolutions now offers a predictive analysis platform in which real-time and historical data of machines and plants as well as contextual information of operational and environmental conditions can be stored, standardized, processed, analyzed, validated and reflected back in a clear and understandable form (figure 1).

Figure 1: Software conception of asset analytics (talpasolutions)

Mining companies as owners and users of machines and equipment benefit from such solutions, currently under development, as it allows condition and performance monitoring of individual machines and fleets. The assets can be analyzed by health scores, asset benchmarking, predictive information on maintenance cycles and spare parts stocking and ordering, trends and forecasts relevant to planning with regard to downtimes, operational breakdowns and interruptions, consumption of auxiliary and operating materials as well as energy, availability and utilization rates.

The platform enables OEMs and service companies in the mining industry to create new service offerings, such as refined condition and performance monitoring, display of trends and forecasts relevant to planning with regard to downtimes, operational disruptions and interruptions, consumption of consumables and energy, predictive diagnostic and repair solutions, optimization of spare parts stocking and delivery.
1.3 Case study

talpa solutions has been conducting a number of projects in the mining industry and has developed a clear way forward to tackle the different challenges while introducing digitalization in a mine in operation.

The following shall briefly present the challenges and how the project was implemented exemplary in an Estonian oil shale underground mine by talpa solutions and indurad7.

In this particular project the mine’s use case8 was to digitize a roof bolter of Nordmeyer SMAG Mining & Drilling Technologies GmbH9 in order to monitor its efficiency and to take operational decisions in a more accurate and faster pace. In the same time, the effort required for manual reports and analyses should be avoided.

1.4 Data gathering and transmission

Prior to starting the project, the main challenges to overcome was to ensure automated data transfer from the vehicle to the cloud-based platform. Following was needed:

One network access

A digital interface to the machine

A "data pipeline" for the actual data transfer

In the specific case, the mine operator provided a WLAN hotspot in the underground maintenance area. The machine data is therefore transferred cyclically, usually between shifts when the vehicle was out of operations and during maintenance. It has been decided to install two WLAN directional antennas on the wall to allow the machine interface to be connected to the maintenance area and the vehicle's parking area in the travel section.

In order to establish a reliable physical data interface an industrial PC (IPC) – iRPU-C (RadarProcessUnit-Compact10) - from indurad was mounted on the vehicle and connected to the CANBus system. Further, the roof bolter has been retrofitted with a speed sensor in order to achieve higher analytical accuracy in connection with underground positioning.

As the iRPU-C is equipped with a SSD hard disk drive intermediate machine data can be stored.

For localization of the roof bolter the vehicle was equipped with 2 additional antennas (iRTT-AU/RadioTransponderTag-AntennaUnit11) at the bow and stern of the machine which communicated with geotags (iRTT-CE/RadioTransponderTag-ClientEquipment) which were installed at suitable points in the mine section. The retrofitted roof bolter then was ready to gather and transmit a broad range of data (figure 2).

7 indurad GmbH, Aachen. https://indurad.com
9 NORDMEYER SMAG Mining & Drilling Technologies GmbH. https://www.nordmeyer-smag.de/
10 indurad iRPU-Compact; https://indurad.com/technology/sensors/irpu/
11 indurad iRTT-AU; https://indurad.com/technology/sensors/irtt/
To comply with the mine’s high data security requirements 2 separate VPN connections were established: one with the mine’s intranet (machine to data server) and another for transferring the data to the external analysis platform. To ensure data loss during a potential disruption from the internet an additional data server was set up on the mine’s intranet (figure 3) using an iRPU-D (RadarProcessingUnit-Demonstration), which has an SSD hard disk for intermediate storage of the data as well and which is connected to the customer’s intranet via a cable connection.

To allow an accurate data analysis of historical and contextual data, such as shift reports, web interfaces and automated applications were provided for uploading.
1.5 **Data processing**

Prior to run analytics procedure digitization faces the challenge to process the original data, which in this case were generated in highly compressed binary format according the J1939 standard, into a human readable format. The conversion was performed on talpasolutions’ platform. The data converted in this way were then categorized according to their origin and expressiveness in order to be able to carry out the accurate analysis.

Storing and processing the increasing data require constantly growing storage and computing capacities which are offered as-a-service by various tech companies.

1.6 **Data analysis and visualization**

Once the data have been preprocessed the actual analysis of the data is carried out applying specific algorithms and automated statistics.

In order to create valuable insights it is of upmost necessity to gain a fully and deep understanding of the machine in operation and how the individual sensor data on the vehicle and in the mining sector contributes. The individual sensors do indeed provide information about the individual machine components and its condition. However, how efficiently a working process is operated, can only be analyzed by the joint evaluation of different sensor values in the form of data models (figure 4).

![Diagram](image)

**Figure 4: Translating machine data into operational insights (talpasolutions)**

In the specific case of the roof bolter it was necessary to establish a full understanding of the 2 main operating tasks: “drilling boreholes” and “setting roof bolts” besides to the machine being travelling between the mining sections and/or the maintenance area. In order to provide valuable information on efficiency and productivity of the roof bolter, it is essential to link the machine data with the localization data.
A comprehensive visualization of the analysis (figure 5) has been chosen to demonstrate the status of the roof bolter in 4 categories:

- idle time, i.e. the time in which the machine electrically on power but not active;
- machine off-time, i.e. the time in which neither diesel engine or hydraulics are switched on;
- travelling time, i.e. the time in which the machine is moving within the mining section;
- working time, to be further elaborated below.

What kind of activity the roof bolter is performing and where it is located is visualized in the 2 upper time series in figure 5. This example shows a substantial time of idle and travelling time at the beginning and end of the shift which is due to recharging with rock roof bolts, nuts, resin capsules etc. However, this relatively shallow analyzing depth and visualization already leads to the potential optimization of the working procedures.

Since the focus in this project was to enhance the efficiency of the drilling process the operating mode was further investigating drilling and bolting over 30 sensor signals. The breakdown of activities can be seen in the table and bar chart in the lower middle and part of figure 5. Core activity of the roof bolter in this shift counts for approx. 30% of the shift time. On the lower left part the machines locations is shown together with the number of drill holes and bolts in this section. Further detailed analysis on drilling and bolt setting activities are provided in separate applications.
1.7 Conclusion

This exemplary project which was only performed on one mining vehicle already demonstrates the potential to increase transparency of the mining process and the use of machines. Based on those analyses the mine was already able to implement different measures for improvement, e.g. amendments of shift duration, ordering and stocking of bolts and drilling materials; proof of consumption of bolts, improved activity records and key performance indicators.

A constantly growing data base in which real-time data are integrated and processed utilizing statistical mathematical and deep learning algorithm incrementally enhance the quality and value of the information. Further insights will be generated by integrating additional equipment of same and different machines types and from different manufacturers.

talpasolutions is convinced that the integration of sensor-equipped and -supported machines and monitoring systems in mining coupled with real-time data analytics will lead to actual insights and intelligent decision-making processes and a further step towards automated, 100 % safety and thus more productivity and resource efficient mining industry.

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Testing of prototype robot UX-1a for exploration and mapping of flooded underground mines

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ABSTRACT:

UX-1a is the first prototype robot, from a multi-robotic platform, that has been built by the UNEXMIN research group. UNEXMIN is a Horizon 2020 project which aims to develop an autonomous robotic system for exploration and mapping of flooded underground mines. For the purpose of testing the prototype robot UX-1a in a real-life environment four flooded mines have been selected across Europe, with gradual increase of harshness of the conditions (i.e. accessibility, the extent of tunnel network system, potential for robot recovery in the case of malfunction etc.). To date the robot has been successfully tested in two mines. The first trial was carried out in a pegmatite mine Kaatiala in Finland (June 2018) and the second test has been conducted in an historical Mercury mine in Slovenia, the Idrija mine (September 2018). The research group has in March 2019 finished the first part of the third trial in the old uranium mine of Urgeiriça in Portugal. The last test is planned in the old copper mine in Ecton in the United Kingdom.

The robot’s spherical shape, small dimensions and a robust hull allows it to explore and collect geo-scientific information from parts of the underground mines that are otherwise almost impossible to reach, without major costs such as dewatering. The diameter of the robot is only 600mm and the maximum working depth is 500 metres. Its eight thrusters give the robot a traveling speed of up to 1 m/sec. The robot’s pitch angle (around vertical axis) is controlled and can be changed during dives with a pendulum subsystem. A ballast system that is installed in the UX-1a helps the robot to save on electric energy during its vertical motions, extending mission times up to 5 hours. It consists of a ballast tank, reservoir and a pump. UX-1a has a complex navigational system that helps manoeuvre the ro-
bot in very harsh underground environments. During the dives the vehicle is able to operate in complete darkness, murky waters and in areas containing different debris or obstacles due to its diversified instrumentation. To prevent the robot getting damaged by loose obstacles and old infrastructure, the system is able to detect small size objects.

As the main objective of UX1-a is to explore underground mines and to collect geo-scientific data, which will help geologists to better identify future drilling targets, an array of scientific instruments is installed in the robot. UX-1a has the capability of measuring water’s temperature, pressure, pH and electrical conductivity, magnetic fields and gamma radiation levels. By using its multispectral and UV fluorescence imaging units it is also be able to identify various minerals in the mine’s walls. During the first two trials different navigational systems and scientific instruments have been tested in real life environments. After each test the robot went through recalibration and system improvements, before facing a more challenging environment of the next pilot in the Urgeiriça mine.

The first trial was carried out in June 2018 in an abundant pegmatite mine Kaatiala in Finland. Kaatiala is a flooded open pit mine with a maximum depth of approximately 30 metres, that continues into a number of underground tunnels down to approximately 40 metres. Currently the mine site is a touristic attraction for recreational scuba divers. This open pit mine was selected as a first test site due to its easy accessibility, large tunnels without debris, non-complicated tunnel network and clear waters. Its depth allowed an easy recovery of the robot by a scuba-divers rescue team in case of a malfunction or in case it could not return to the surface due to other problems. Its proximity to the Tampere University of Technology (TUT) was also useful in case some lab adjustments or repairs had to be done to the robot or its instrumentation during the pilot.

At the first trial site, two locations were used for the test dives. The first site was located at the shallow part of the quarry, where the team tested the operation of UX-1a in shallow waters. After a number of dry tests during which the team tested operation of different sub-systems after transport, basic robot functionality tests were conducted, including testings of leakage, buoyancy and locomotion. These tests all gave positive results. Throughout the dives at the Kaatiala mine, the robot was connected to the control unit, set up on the land site, via an umbilical ethernet connection. This hard-wired connection allowed team members to operate and navigate the robot for an increased security of operations.

The second part of the tests was carried out at the deeper end of the quarry, where UX-1a was tested in greater depths and in the mine tunnels. The tests at the deeper part of the mine were more challenging as the robot had to be manoeuvred by relying solely on instrumentation. The robot was diving in 0.5 metre to 2 metre steps. The dives were approximately two hours long and the robot reached the maximum depth of app. 30 metres where it successfully mapped the old underground tunnel. Once under the surface, the robot was controlled using sonar and scanner images obtained with UX-1a’s instrumentation. The sonar images were constantly refreshed and showed any potential obstacles and old underground tunnels. The members of the control team were testing the depth controller and were constantly monitoring the batteries’ charge state. During the deep dives, the robot instrumentation was used to map the vertical submerged wall, the entrance to the tunnels and the areas inside the tunnels. 3D point clouds were obtained with Multibeam M3 sonar,
and visualised using special computer software in real time. The data processing software automatically updated point clouds according to the robot’s position, and attached newly collected point clouds, regardless of the change in robot’s location. Due to the limited capacity of the processing software and computer memory, point cloud data needed to be reset from time to time. These point clouds, combined with the visual and sonar data, represented the main input for the robot navigation. All the navigational systems, except the laser stripe system, have been proven to be working well and the robot returned to the surface without intervention of the recovery team of divers, on every diving mission. Besides that, the team got a better impression of the robot’s actual capabilities and got valuable experiences in navigating the robot without visual contact. Also, the work related to UX-1a maintenance (i.e. batteries replacement, re-calibration, data download etc.) was done faster after the trials, when compared to the period before.

The second series of tests with the first prototype robot were done in September 2018 in a closed and partially flooded historical underground mercury mine in Idrija in Slovenia. The mine is also listed as part of the UNESCO World Heritage site, which made the non-contact, non-damaging nature of the robot a must. The objective of the second trial was to test the operation of the prototype in a much more challenging real-life environment when compared to the first test site in the Kaatiala mine in Finland. The Idrija mine is an underground mine with limited visibility and narrow passages. The part of the flooded shaft where the robot was tested also contained lots of debris and old structural beams and cables which had to be avoided by the robot during the dives not to damage the equipment nor the mine itself.

The test dives were carried out in the main Borba shaft, which is currently used by the mine for pumping and regulating the mine’s water table and for the transportation of miners and maintenance materials to underground level III. Due to limited space, ventilation and electricity, the team had to work on different levels of the mine. Because the mine water, in which the robot was diving, was too murky for the team to utilise UX-1a’s camera system, the operator of the vehicle had to rely solely on the robot’s acoustic and inertial navigational systems.

During the trials a total of eleven dives were made within the span of two weeks. The robot successfully reached the deepest part of the mine shaft, at approximately 27 meters, with exceptional accuracy and gathered data for 3D mapping for offline post processing. For the purpose of testing UX-1a’s multispectral unit (MSU) the robot had to be manually positioned in front of three different mineral sample boards which were previously submerged into the shaft water. The test was conducted on various depths. The measurements were repeated several times to ensure that all images were available for post-processing. During the MSU tests the reflections from the water surface could generate false data during measurement, so the exact position of the board needed to be precisely adjusted. The time sequence of the different light sources was also successfully tested. The most challenging test was done at the last dive, where full UX-1 autonomy was tested. By setting up navigation waypoints the robot needed to dive on its own. The mission was successful, and the robot returned safely back to the surface, marking a major accomplishment in the project’s development.
As of March 2019, the research team is in the middle of the third trial that is taking place in a uranium mine in Urgeiriça, Portugal. The main objective of the third trial is to continue testing the robot’s autonomy and all scientific instrumentation that is installed in it. Since the Idrija trials a second robot, UX-1b, has been assembled and it is also going to be tested in Urgeiriça. For the fourth trial, which is planned in the historical copper mine Ecton in the UK in May 2019, the research team is planning the most ambitious demonstration of the capabilities of the robot platform that has been developed as part of the UNEXMIN project. The objective of the final trial is to conduct a detailed survey of the entire Ecton mine using three robots, that are going to be exploring the mine simultaneously.

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