Sustainable Energy Authority of Ireland

National Energy Research, Development & Demonstration Funding Programme

FINAL REPORT TEMPLATE

SECTION 1: PROJECT DETAILS – FOR PUBLICATION

Project Title	Increasing energy efficiency of minerals processing operations by advanced sensor-based sorting of ores (ENEROS)
Lead Grantee (Organisation)	Trinity College
Lead Grantee (Name)	Igor Shvets
Final Report Prepared By	Igor Shvets
Report Submission Date	31.05.2023

	Name	**Organisation**
Project Partner(s)		
Collaborators	John Güven	iCRAG, UCD

Project Summary (max 500 words)

Please provide an overview of your project, the context, objectives, key results and outcomes.

The mining industry faces the ever-growing problem of increasing mineral demand while fewer new exploitable deposits are being discovered, reserves continually deplete, and mine grades diminish. The current solution to this is to increase the amount of ore mined and processed to sustain production against the declining quality/grade of ore. The energy cost and carbon footprint of this approach is staggering. There are two main drivers leading to the high energy cost of mining. Firstly, the vast quantities of ore need to be milled into micron-size powder. This is required to liberate the minerals from the

waste rock using the flotation process. Secondly, vast quantities of chemicals are required for the flotation process.

The goal of ENEROS was to develop and validate an ore sorting technology designed to reduce costs and energy footprints of mining operations. We addressed the mining industry's problem of uneconomical deposits and diminishing ore grades, and hence the EU's strategic concerns of the supply of critical materials. The sorting system developed in the project makes use of cutting-edge sensor designs as well as modern machine learning techniques.

The ENEROS technology is potentially applicable to many raw materials that are crucial for the modern society such as copper, lithium, nickel, zinc. Many of these elements are crucial for the development of low carbon energy technologies. For example, lithium is an innovation-critical material of extreme importance to battery technology.

A spectral imaging system was developed by us in the project to capture reflectance spectral images of samples in a scanning fashion intended to be compatible with typical conveyor setups found in the mining industry. Slow (50min) high-SNR reflectance scans were captured of a set of samples designated for fitting models, and faster (10s) scans were captured of another set of samples for inference validation.

Several variations of the proposed classification method were explored on the basis of transforming reflectance into absorbance, and by performing continuum extraction to split spectra into continuum spectra and feature spectra. Models fitted on absorbance data did not perform well on test samples. Continuum spectra (which are commonly disregarded by the literature) produced reliable models, whereas feature spectra (which are commonly used for analysis) did not.

The most straightforward variation using unmodified reflectance spectra exhibited the most reliable inference performance, and outperformed baseline LDA models fitted directly on reflectance spectra or on RGB images. In particular, it generalised more reliably from the training samples to the test samples than the reflectance spectral model (which suffered from overfitting), and provided higher-confidence inferences than the RGB photo model.

Two common unmixing (abundance map generation) algorithms were compared in the context of fitting binary classification models: unconstrained least-squares (UCLS), which may produce unphysical abundance values but is certainly fast enough for real-time use, and fully-constrained least-squares (FCLS), which imposes realistic constraints but is slower. UCLS-based models consistently performed slightly better in inference, which may be due to the normally-distributed statistics of their output matching the assumptions made by LDA on its input.

Keywords (min 3 and max 10)	Mining, ore sorting, ore extraction, machine learning, artificial intelligence

NB – Both Section 1 and Section 2 of this Final Report will be made publicly available in a Final Technical Report uploaded online to the National Energy Research Database.

In the following Section, please provide a clear overview of your project, including details of the key findings, outcomes and recommendations. The section headings below are provided as a guide, please update or add to these as best suits your project.

By submitting this project report to SEAI, you confirm you are happy for Section 1 and Section 2 of this report to be made publicly available. If you wish to request edits to this section in advance of publication, please contact SEAI at EnergyResearch@seai.ie.

SECTION 2: FINAL TECHNICAL REPORT – FOR PUBLICATION (max 10 pages)

2.1 Executive Summary

ENEROS addressed the stated mission of the SEAI "to work with the public, businesses, government and communities to achieve a cleaner energy future" and aligned with their aims to bring about a low carbon economy through measures and activities focussed on the transition to a smarter and more sustainable energy future. The project was aligned with the following two objectives of the SEAI National Energy RD&D Funding Programme:

●Accelerate the development and deployment in the Irish marketplace of competitive energy-related products, processes and systems
●Grow Ireland's national capacity to access, develop and apply international class energy RD&D

The project aimed to develop and test technology that can improve energy efficiency of minerals processing operations.

Ireland has a strong mining industry; it contains the Tara Mines Boliden the largest zinc concentrate producer in Europe, processing 7,000 tons of ore daily. There are also several mineral processing companies awaiting licences and some 600 (!) prospecting licenses active or being applied for.

Much of the extremely high energy demand and carbon footprint of mineral processing is due to the crushing and milling the ore into a powder. This is required to liberate particles of recoverable mineral via the flotation process. This project strived to reduce the amount of ore that needs to be processed in this way, reducing the energy consumption of this operation. Knowledge developed by the project can be of benefit to the public good as it could be applied by numerous companies.
The mining industry faces the ever-growing problem of increasing mineral demand while fewer new exploitable deposits are being discovered, reserves continually deplete, and mine grades diminish. The current solution to this is to increase the amount of ore mined and processed to

sustain production against the declining quality/grade of ore. The energy cost and carbon footprint of this approach is staggering.

There are two main drivers leading to high the energy cost of mining. Firstly, the vast quantities of ore need to be milled into micron-size powder. There is massive energy penalty required to mill the ore for the hydrometallurgy process. This is required to liberate the minerals from the waste rock using the flotation process. Secondly, vast quantities of chemicals are required for the flotation process.

ENEROS developed an ore sorting technology designed to reduce costs and energy footprints of mining operations. The project addressed the mining industry's problem of uneconomical deposits and diminishing ore grades, and hence the EU's strategic concerns of the supply of critical materials. The sorting system makes use of cutting-edge optical sensor designs having spectral analysis capability as well as modern machine learning techniques.

2.2 Introduction to Project

It is common practice in the minerals processing industry that material extracted from a mine forms a diluted blend of rocks comprising valuable ore and barren rocks, i.e. host rock surrounding the ore. These are mixed in one stream on a conveyor belt or in a bin taken out of a mine. Preferably, these need to be separated to avoid needless costly processing of barren rock that produces no useful mineral output. Often the situation is even more complicated where the ore pieces include ores of several different types, and these need to be processed using different industrial pathways. For example, the "Beralt Tin and Wolfram" mine in Portugal simultaneously extracts ores of three different minerals containing tungsten, tin, and copper, and this situation is rather typical.

The separation or sorting of mined material into valuable ore and barren rocks without value has been a common practice in the minerals processing industry since its inception. For a long time, the common approach was to lay the rocks from a mine along a surface and then collect the ones that appear valuable by hand, discarding the rest. This was heavy manual work and often child labour was deployed in this industrial process. Later, with the introduction of machinery, the rocks moved onto a conveyor belt and workers positioned along the conveyor belt picked up the desired rocks for further processing or alternatively removed the unwanted rocks from the conveyor to be discarded. This was still a labour-intense and dangerous job. The separation of ore pieces from waste rocks was done by a worker's manual inspection based on rock colour, texture and appearance.

Very often differentiating between the ore and barren host rock is not straightforward, as the same mineral may have several different kinds of visual appearance, and the decision on the sorting needs to be based on a combination of several parameters. As more and more industrial processes have become automated, there have been attempts to introduce separation of the ores using simple sensors. This approach is generally not successful. Colour alone is a poor indication of the type of ore. To illustrate this point, figure below shows three examples of petalite ($LiAlSi4O10$), an important lithium-containing ore that can have different visual appearances. Similar diversity of appearance is common for many other minerals.

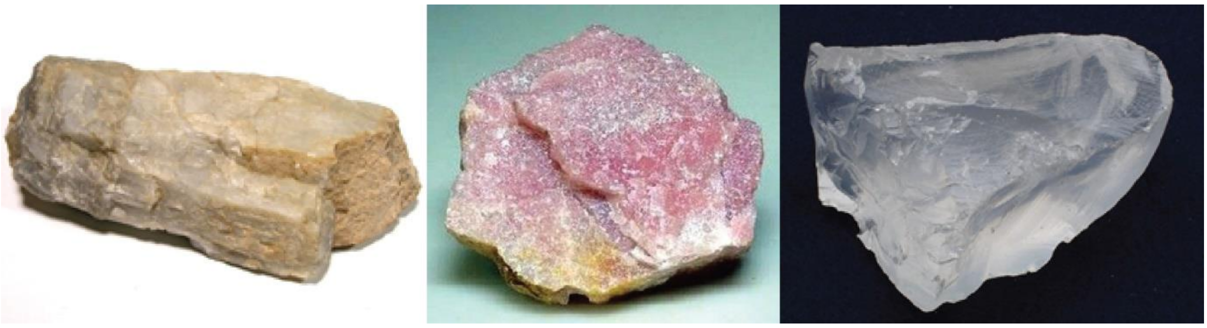


Figure caption: Examples of three different pieces of lithium ore petalite having rather different appearance and yet represented by the same crystallographic structure and chemical formula ($LiAlSi4O10$).

Somewhat more advanced technologies for ore sorting have become available in recent years (e.g. Outotec/TOMRA, Steinert, NextOre, or Comex). These are typically based on the detection of X-rays transmitted through the material. The transmission of X-rays through materials (termed "X-ray transmission density") can be indicative of rock type in certain cases, however often it is not a good indication of the ore composition. There are other inherent limitations of these ore sorting technologies and as a result they have not achieved widespread acceptance in the mining industry.

The main limitation of current technologies based on X-ray transmission is the need to crush the material feed into excessively small particle size, down to a few centimetres, which introduces an extra costly step in ore processing and reduces the throughput of the plant. For larger particle size, the selectivity based on X-ray transmission declines. Additionally, the small particle size requirement makes the industry practice of autogenous milling difficult or impossible.

Sorters that can handle larger particle sizes commonly use fairly primitive and imprecise sensors (e.g. colour sensors), and rigidly defined selection criteria for the sorting process. Such rigid sorting algorithms do not allow for the flexibility necessary for optimal separation of ore from waste rock at different sections of a mine. Indeed, even within a given orebody there is significant variability in the ore grade, texture and composition. The demand for raw materials increases steadily and the availability of ore reserves declines. The manual separation of ores on a conveyor belt is now out of the question due to work safety considerations. A fast moving conveyor belt loaded with rocks is very dangerous and cannot be touched. It is therefore currently the industry norm that the entire quantity of rock removed from a mine is processed in order to extract the tiny percentage of valuable ore. Let us consider the example of tungsten, a strategic metal and an essential constituent part of high performance steel.

The world annual production of tungsten is 78,000 tons. Tungsten alloyed in steel cannot be recycled and therefore the long term trend in the price of tungsten is upwards. Reserves of tungsten ore have been depleted worldwide. For example the company “Beralt Tin and Wolfram” in Portugal is one of the largest producers of tungsten ore concentrate, wolframite ($(FeMn)WO_4$) in Europe. The applicant visited the mine and studied the ore processing cycle. The company does not deploy any sorting, and all the ore lifted from the mine is subjected to crushing and grinding to a particle size of some 5 mm for separation. This process is very common for such mines worldwide and routinely producers do not use any ore sorting prior to grinding material into small particles.

The content of wolframite in the mine gradually declines as the best ore reserves have been depleted. The percentage of wolframite in the ore taken from the mine is now at the level of just 0.14%. When the production of tungsten started on site in 1930s, the percentage of worlframite in the ore/rock extracted in this mine was 0.45%. We therefore see a decline in the quality of the ore by a factor of 3 since the start of the operations. This situation is similar for other tungsten-producing mines. One can see that in order to extract the 0.14% that is useful ore, one has to crush the entire content of rock of which over 99% is a barren rock.

The energy associated with grinding rock into small particles is massive. The smaller the final particle size, the greater is the energy required for the milling.

The energy consumption of the rock/ore crusher machine is somewhat dependent on the type of the crusher. However, critically it depends on the size of the grains the machine is expected to produce. The size of the rock grains produced by the machine is defined by the screen aperture size, the final step in the crushing process. The representative figures for a cone crusher are 0.8 kWH per ton of rock for 10 mm rock and this escalates to the value of 1.4 kWh per ton if the grain size is reduced to 6.7 mm [7]. Further reduction of the grain size leads to a massive increase in the energy per ton of the rock processed. The figures for the energy consumption also depend on the type of the rock processed. It is clear that to reduce the energy costs of production of elements, one would like to avoid ore processing technologies that require crushing the rock into small grain size material.

Once the desired material has been extracted from the milled rock removed from the mine, the remaining waste often forms massive tailings either in the form of artificial mountains or in the form of tailings ponds containing water, chemicals used for the separation and the pulverised rock. There are significant environmental consequences of these including the risk of collapse of the dams securing the tailings ponds.

2.3 Project Objectives

The main objectives of the project were:

1. Develop the technology enabling separation of ore and barren rock into separate streams without the need for crushing and milling the entire stream of materials removed from a mine thus achieving mechanical pre-concentration for ores. The underlying technology achieves this pre-concentration by sorting a feed of individual rocks into waste and product streams based on an analysis of their composition, prior to any invasive processing. In this way, the amount of ore sent for energy costly and environmentally taxing processing is reduced.

2. Validate this technology under real industrial conditions at Tara Mines using zinc ore as the demonstrator of the technology's capability.

3. Assist Irish company Tara Mines in assessing the viability of this technology for the reduction of the energy bills associated with milling the ore.

4. Prepare for the commercial deployment of this technology at other minerals processing companies in European Union and in other geographies.

2.4 Summary of Key Findings/Outcomes

The proposed method for the first time applies the established remote sensing techniques of virtual dimensionality estimation, endmember extraction and abundance map generation in conjunction with linear discriminant analysis to produce abundance-based classification models capable of real-time differentiation between two classes of mineral samples for the purposes of ore sorting. The models were tested on lithium-bearing lepidolite samples and barren granite samples from Gonçalo, Portugal.

Figure caption: Lepidolite sample collection site and process

A push-broom spectral imaging system was designed to capture reflectance spectral images of samples in a scanning fashion intended to be compatible with typical conveyor setups found in the mining industry. Slow (50min) high-SNR reflectance scans were captured of a set of samples designated for fitting models, and faster (10s) scans were captured of another set of samples for inference validation.

Several variations of the proposed classification method were explored on the basis of transforming reflectance into absorbance, and by performing continuum extraction to split spectra into continuum spectra and feature spectra. Models fitted on absorbance data did not perform well on test samples. Continuum spectra (which are commonly disregarded the literature) produced fairly reliable models, whereas feature spectra (which are commonly used for analysis) did not.

The most straightforward variation using unmodified reflectance spectra exhibited the most reliable inference performance, and outperformed baseline LDA models fitted directly on reflectance spectra or on RGB images. In particular, it generalised more reliably from the training samples to the test samples than the reflectance spectral model (which suffered from overfitting), and provided higher-confidence inferences than the RGB photo model.

As an additional benefit of transforming the spectral data into a lower-dimensional space of spectral components, individual endmembers can be explicitly suppressed when fitting a model. This was demonstrated on the example of contamination by markers which were used to write labels on the samples. This kind of manual intervention is entirely optional, as the fitting process can in principle be completely automated, only requiring two known sets of samples to be distinguished.

Two common unmixing (abundance map generation) algorithms were compared in the context of fitting binary classification models (figure below): unconstrained least-squares (UCLS), which may produce unphysical abundance values but is certainly fast enough for real-time use, and fully-constrained least-squares (FCLS), which imposes realistic constraints but is slower. UCLS-based models consistently performed slightly better in inference, which may be due to the normally-distributed statistics of their output matching the assumptions made by LDA on its input.

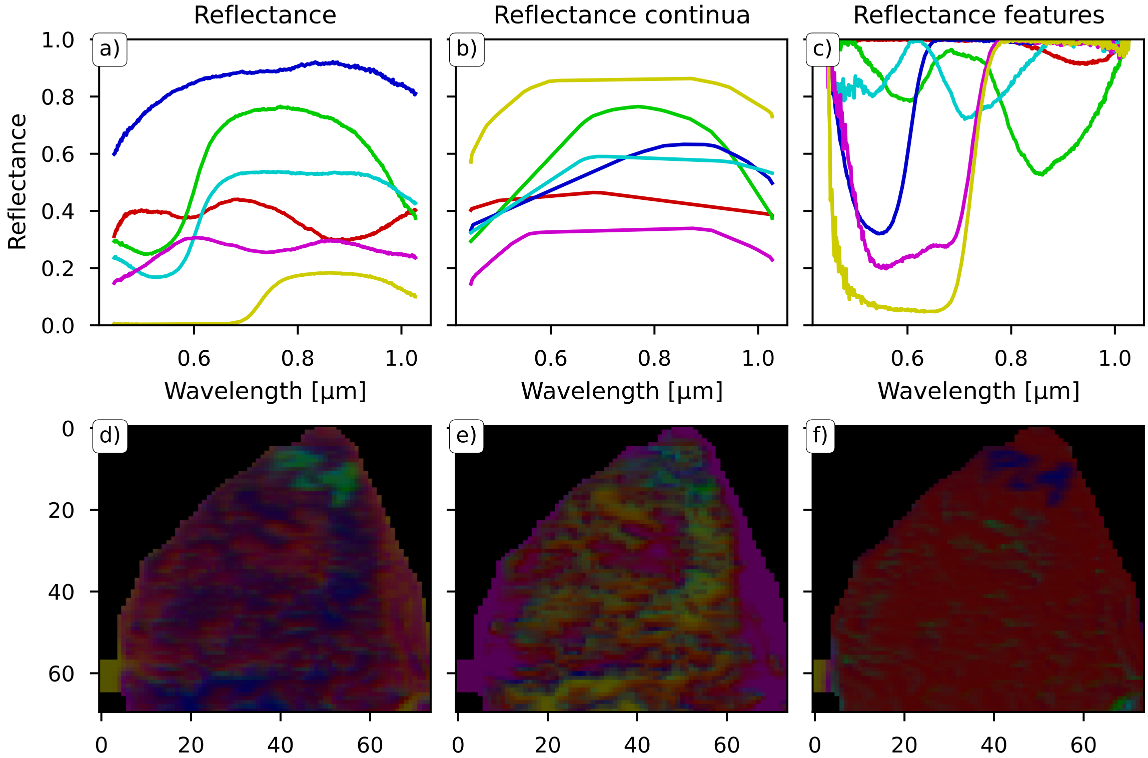


Figure caption: Extracted reflectance endmembers for PL1-A and associated false-colour representation with each endmember's abundance mapped to red, green, blue, cyan, magenta and yellow. a)+d): Reflectance endmembers with map. b)+e): Reflectance continua endmembers with map. c)+f): Reflectance features endmembers with map.

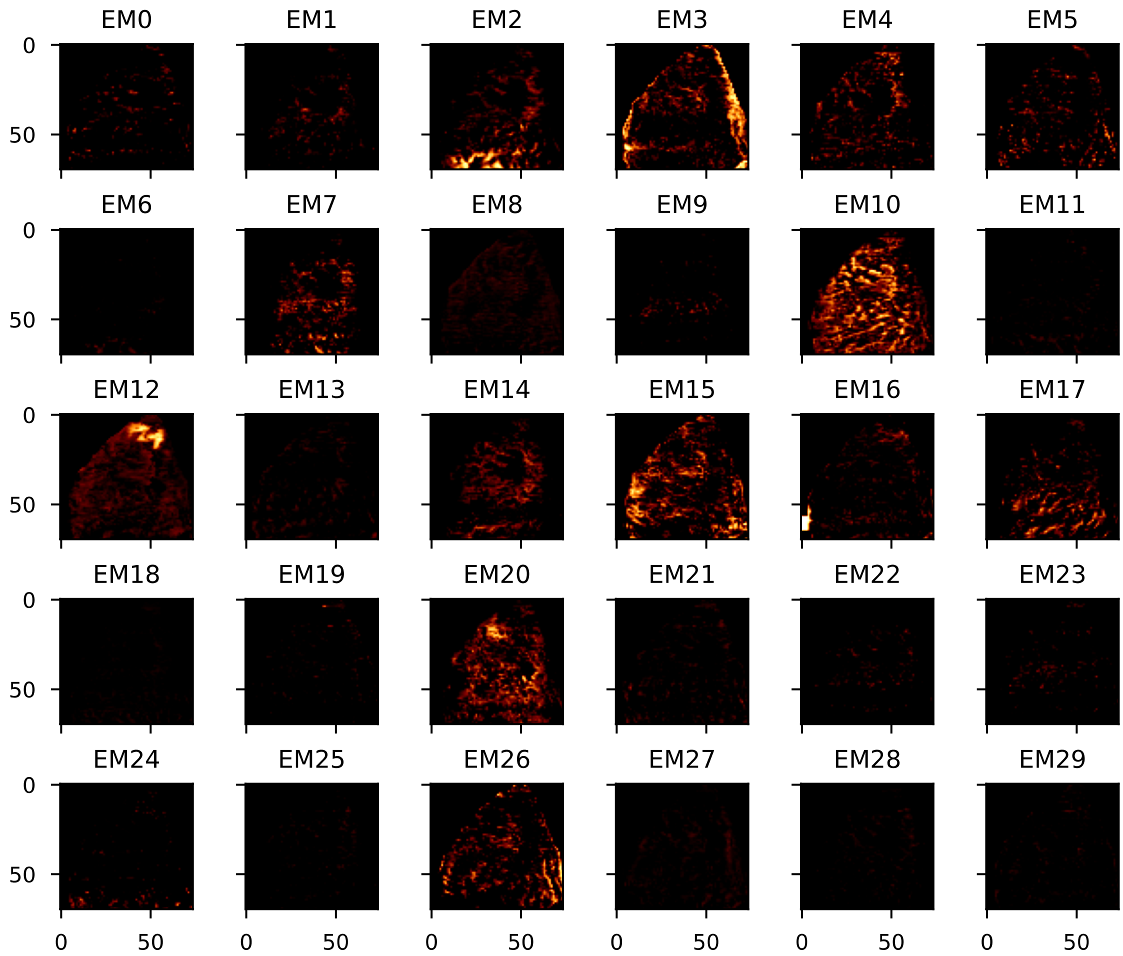


Figure caption: FCLS-generated abundance maps for PL1-A of each reflectance endmember of the common spectral library. Note the pink label endmember EM12, the scene background endmember EM16 (see Figure 9, right) and the potential lepidolite endmember EM20.

While the imaging spectrometer was custom-designed for the purposes of prototyping ore sorting methods, it was far from ideal. Its optics exhibited chromatic distortion which tended to produce curved projections of spectra, in particular, near the edges of the frame. The spectral resolution was also not constant across the frame. Low sensitivity of the system in the ultraviolet and violet parts of the spectrum resulted in unacceptably low SNR there. The imaging sensor had unnecessarily high resolution and no cooling. Unidentified dark horizontal line artifacts were also prominent in raw captures, although they were easily corrected for. A professionally designed and calibrated push-broom spectral imaging system would surely yield better results. It would also be interesting to apply the proposed method to other wavelength ranges such as NIR or SWIR, and to fluorescence in place of (or in addition to) reflectance.

The method was evaluated on the basis of samples from only one orebody. It would be highly important to test its generalisability by applying it to more diverse types of ore.

There are newer techniques developed in recent years in the field of remote sensing which are attractive for ore sorting applications. More advanced endmember extraction techniques could be applied, such as ACEE (Xu, 2014), which takes spatial information into account. Multi-sensor data could be combined such as in (Lorenz, 2019) to improve spatial resolution of spectral images.

Further incorporation of external information into abundance-based classification models could be attempted. Perhaps the contribution of individual high-value endmembers could be boosted, analogously as contaminant endmembers were suppressed here.

Apart from continuum extraction/removal and reflectance transformation to absorbance, no common spectral processing techniques were investigated in the context of abundance-based classification. For example, multiplicative scatter correction (Isaksson, 1988) could be applied to compensate for variability in particle size distributions.

In this study, only linear discriminant analysis was used for simplicity. Many other binary classification methods are available and should be compared rigorously in this context given the statistics of abundance data.

It may be possible to relax the only condition imposed on the input, which is that two separate classes of samples are prepared for fitting. Using the presented methods of creating a spectral library on a single unlabelled set of samples and generating abundance maps for them, the resulting abundance values (or their fitted distribution parameters) could be automatically clustered into two (or more) distinct groups which could then be used to fit a classifier.

The binary classification of pixels/samples could be replaced with a regression of the concentration of the desired material in a sample. This would require the scanning of samples of known (and varying) concentrations, most likely to be determined using destructive methods.

Abundances can be reasonably seen to follow multivariate normal distributions (in the case of UCLS unmixing) or Dirichlet distributions (in the case of FCLS unmixing). Fitting the parameters of these distributions (for estimation of Dirichlet parameters see (Minka, 2000) and for goodness-of-fit tests see (Li, 2015)) would allow the generation of unlimited amounts of synthetic pixels, which could be used to train more complicated machine learning systems such as deep neural networks.

The presented abundance-based classification methods can be thought of as implementing a dimensionality reduction technique (from 448 spectral channels to 30 spectral components), similar to the way that neural networks typically incorporate a lower-dimensionality latent space representation of the input data. It might be an interesting question whether a deep neural network could be trained on simulated arbitrary mineral mixtures to perform this dimensionality reduction in an unsupervised way, replacing the step of endmember extraction and automatically generating a spectral library for any given orebody.

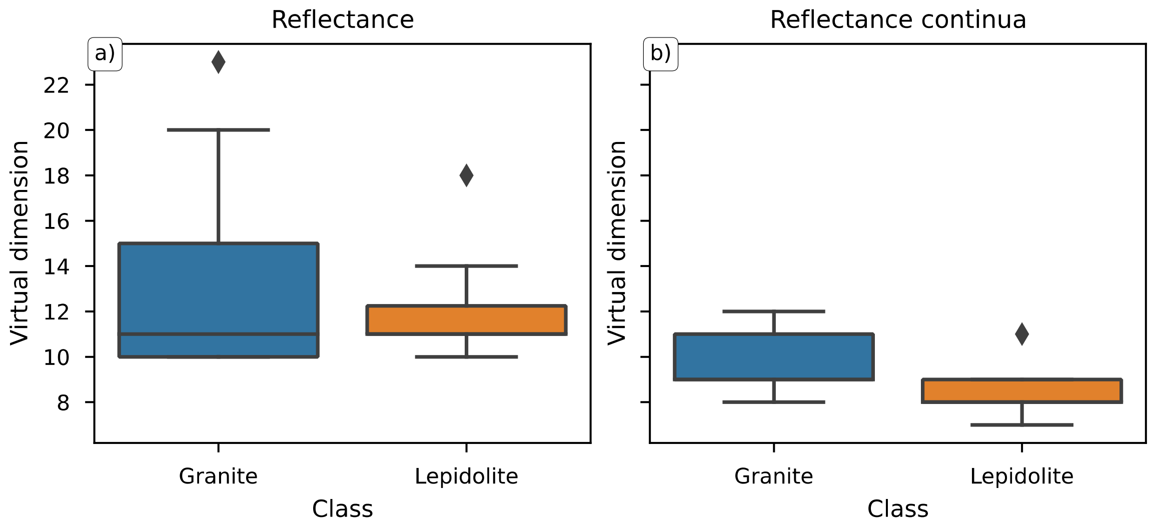
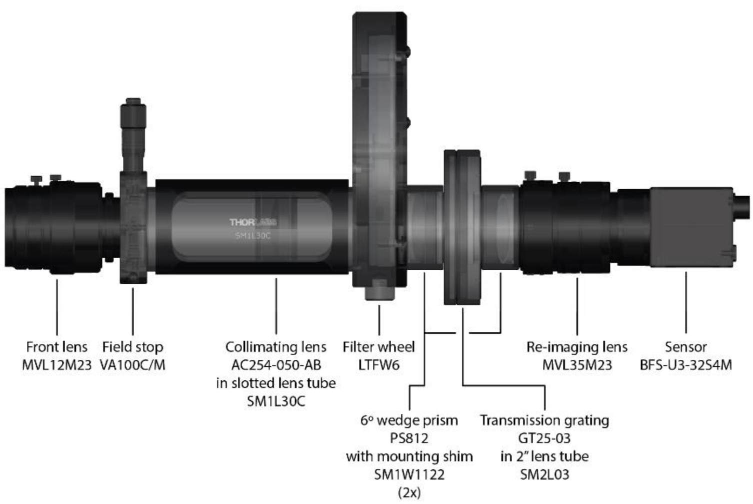


Figure caption: Boxplots of estimated virtual dimension of each class of sample in the reflectance pipeline for a) original spectra and b) continuum-extracted spectra. No virtual dimension could be calculated for the feature spectra using available algorithms.

Innovation 1. Imaging spectrometer for scanning of ore samples integrated with a conveyor belt. Schematics of the scanner is shown in Fig. below.



Characteristics of the spectrometer are as follows: imaging distance of 24cm, imaging focal length of 12mm at a distance of 24cm, this results in a width of the imaged line of 800µm. The distance advanced by the stage at each step was matched to this value. At the maximum stage travel of 60mm this implies 75 steps per scan. The bit depth of the imaging sensor was set to its maximum value of 12 bits, stored as 16-bit unsigned integers at a resolution of 2048 by 1536 pixels (implying exactly 6MiB per frame). The 99% reflectance target was used to identify the upper limit of the exposure time that avoids sensor saturation (note that specular reflection in a sample can still cause saturation). An exposure time of 250ms at a gain of 10 was chosen.

Innovation 2. Software for the identification of the minerals based on machine learning algorithm and machine training.

Results obtained using this software are illustrated in Fig below.

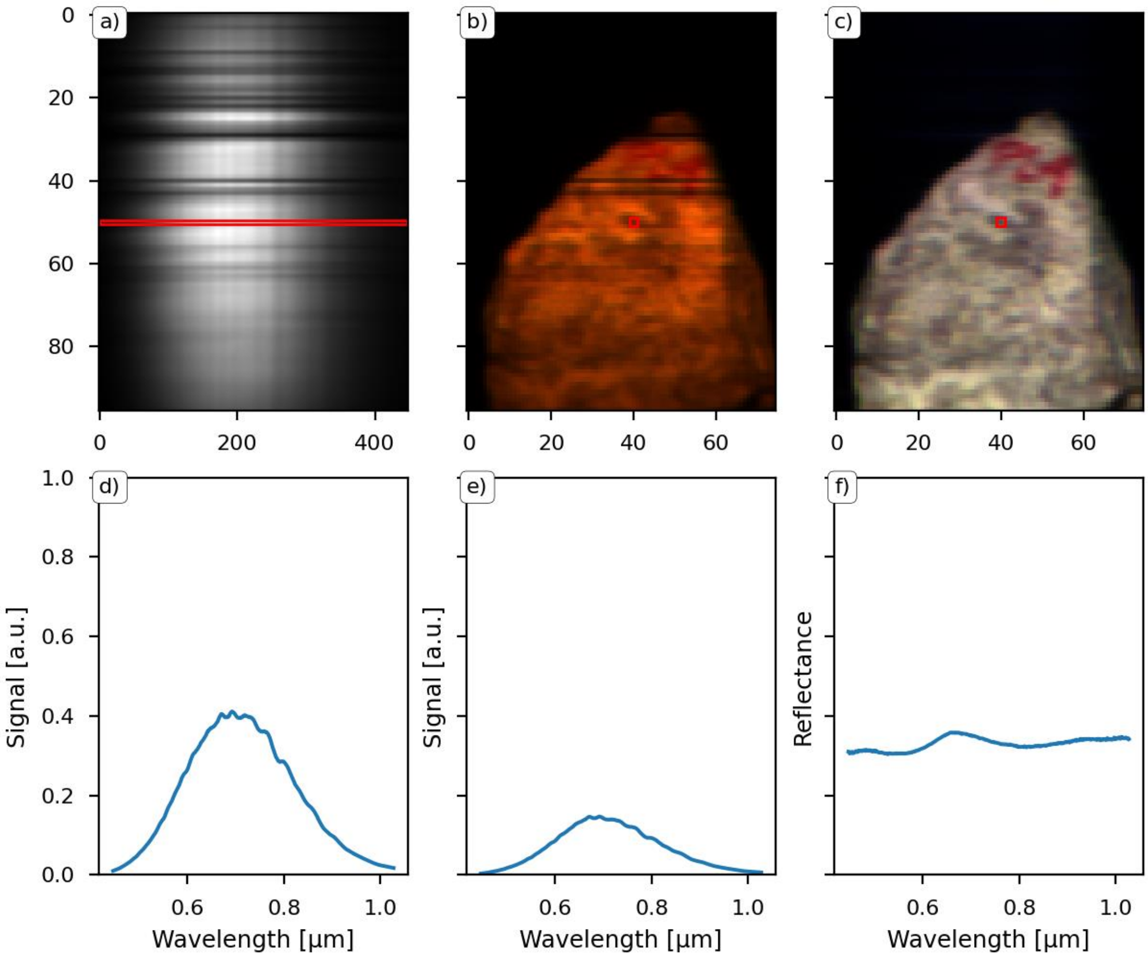


Illustration of white-reference application. a)+d) White-reference stack and signal along the highlighted pixel row. b)+e) Reconstructed RGB image of PL1-A scan before division by white reference and signal at the highlighted pixel. c)+f) Reconstructed RGB image of PL1-A scan after division by white reference and signal at the highlighted pixel.

Innovation 3. Lab-scale spectral imaging hardware platform

A custom imaging spectrometer has been designed for the application. It uses filters to provide flexibility of the type of measurement and its frame rate and spatial and spectral resolution can be tuned to fit a desired conveyor belt speed.

Innovation 4. Software framework for inversion of scanned spectroscopic projections
A new extension to CTIS called SCTIS has been developed, along with new representation of the sparse matrices involved. Sparse pseudoinversion of these matrices has been achieved, enabling real-time operation of the SCTIS system.

Innovation 5. Aggregated mineral spectral database
Publicly available spectroscopic datasets have been collated and homogenised to provide a solid foundation for training a mineral-identifying neural network.

2.5 Project Impact

Clearly position the impact of your project with reference to the needs of the Irish Energy Sector, national and international policy objectives, and SEAI's remit.

Discuss the key impacts of your project: societal, economic, technological or otherwise. Clearly identify and highlight the value of your project in the wider context.

The projects impact is focussed along two areas:

1. Development of energy saving technologies and industrial processes. Energy required to crush ore containing rock into powder is massive and is the main contributor to the carbon footprint of the mining industry. The project results are aimed at reducing this contribution.
2. Development of technologies and industrial processes reducing adverse environmental impact. Mining and metal production industry routinely uses hydrometallurgical processes. They require substantial amounts of chemicals and these have environmental penalty. The project results will allow to improve the grade of the ore feedstock sent for the hydrometallurgical process and this will reduce the amount of chemicals to be used.

2.6 Recommendations

Please highlight any implications/opportunities/recommendations for Ireland (e.g., for policy makers, for the research community, for industry) based on the work carried out in the project.

There is substantial concern around the security of supply of many elements. One could summarise the situation in one sentence: in the era of renewable energy technologies metals is “the new oil”. There are multiple elements that in critically short in supply such as Li, Cu, Nd, Pr, V, Ni, Mn, Co and others. This concern is particularly severe in Europe and other developed world regions. In Europe we need to develop production of these critical elements from our own resources whenever possible. It is clear that not all the elements are available due to lack of suitable geological sites. However, there is a lot more that could be done to make Europe less reliant on supply of minerals and metals from remote regions, some of which are areas of political tensions with Europe.

The project results will allow to improve extraction of metals from ore, work with lower grade ores that could be improved through the process developed in the project. This will have a positive impact on the security of supply. Policy makers need to develop legal framework that is more receptive to the mining and production of critical elements in Europe.

2.7 Conclusions and Next Steps

The project demonstrated successful implementation of the concept of optical identification of the ore grade based on spectroscopic analysis of the sample surface. We have used the ore samples containing the critically important elements Li and W in our studies.

We need to improve the speed of the optical identification to make the technology compatible with the real mining operations requirement.

The next stage should be development of the industrially compatible prototypes of the technology.