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Performance Improvements during Mineral Processing Using Material Fingerprints Derived from Machine Learning—A Conceptual Framework

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Abstract: Material attributes (e.g., chemical composition, mineralogy, texture) are identified as the causative source of variations in the behaviour of mineral processing. That makes them suitable to act as key characteristics to characterise and classify material. Therefore, vast quantities of collected data describing material attributes could help to forecast the behaviour of mineral processing. This paper proposes a conceptual framework that creates a data-driven link between ore and the processing behaviour through the creation of material "fingerprints". A fingerprint is a machine learning-based classification of measured material attributes compared to the range of attributes found within the mine's mineral reserves. The outcome of the classification acts as a label for a machine learning model and contains relevant information, which may identify the root cause of measured differences in processing behaviour. Therefore, this class label can forecast the associated behaviour of mineral processing. Furthermore, insight is given into the confidence of available data originating from different analytical techniques. Taken together, this enhances the understanding of how differences in geology impact metallurgical plant performance. Targeted measurements at low-confidence unit processes and for specific attributes would upgrade the confidence in fingerprints and capabilities to predict plant performance.

Keywords: data confidence; machine learning; material fingerprints; mineral processing; behavioural prediction, mining

1. Introduction

The behaviour of mineral processing is a response to the complex interaction of primary rock attributes, such as chemical composition, mineralogy, texture, and fracturing [1–3]. Therefore, to understand how differences in material attributes impact metallurgical plant performance, novel machine learning (ML) applications could help. However, large datasets are necessary for these ML models. Successively, with these datasets, it is possible to describe the plant blend better and improve metal recovery. Lamberg [4] described a particle-based geometallurgy framework, where small particles are used to link geology and metallurgy. However, in practice, the feed that enters the processing plant is still a blend of different particles and compositions, and the interaction between these particles also plays a vital role in the processing behaviour [5].

The most important characteristics (data sources) of a blend are the primary material attributes, which are obtained during material characterisation. A better understanding of their composition allows for distinguishing between different material classes. For this, interpretation of individual datasets could be done, but this is time-consuming, especially for fused datasets. If all data could be combined, this assembles all the specific characteristics. It reveals the lines between the chemical system and the mineralogical system by partially selecting the important features of each dataset. Several case studies demonstrated the value of mineralogical and textural information through data fusion, for optimisation of process performances such as comminution [6–8]. Based on this success, new ML techniques could reveal the links between the data.

The remaining open questions for the mining industry are which material data are relevant, where to acquire them, how can they be understood, and what is the confidence in them. Therefore, to maximise the data utility for decision-making, the data have to be of high confidence. The authors of Reference [9] could, for example, extract mineral texture for process prediction, and those of Reference [10] were able to separate waste particles from gold ore particles and distinguish between different ore types without measuring the gold concentration. The data do not inherently resemble the potential extractable knowledge and, thus, confidence should be gained in understanding and interpreting it. After appropriate (useful) data selection, much value can be gained from feature selection/engineering (data transformations) [11], whereas these new features better express the specific characteristics of a class of material. Even though this class could be indicative of the material, it lacks direct interpretation due to the transformations. Therefore, to assess the classification value, it is important to have domain knowledge. Domain knowledge can direct the appropriate problems to be solved, identify the appropriate ML techniques, assess the classification outputs, and evaluate metrics of correlation between data variables [12]. Thus, the maximisation of data utility in mining requires an extensive assessment and generation of data confidence and the ability to recognise the degree of confidence at different stages of mining.

This paper attempts to resolve these issues by answering the questions on which types of material attribute data are relevant and what does the moment of acquisition inform about the confidence in material understanding. It also attempts to address how the data can be used for improved behavioural predictions during mineral processing. The aim is to provide a new conceptual framework for material characterisation and to quantify the degree of confidence of whatever the data resembles. Firstly, the degree of confidence of different datasets (or acquisition techniques) and the unit processes in the mining cycle are explained. This may help to identify measurement localities and the required techniques which could upgrade the degree of confidence. Secondly, the concepts are explained for each unit process; finally, additional commodity-related examples are used to illustrate the potential for practical implementation.

2. Methods

Data from different types of material and equipment are collected in a mining operation at regular intervals. The data from the material would directly resemble the effect of equipment on handling this material. Therefore, considering this data flow, the initial data would be generated during the material characterisation. Afterwards, the data (or material attribute classes, fingerprints) can be followed throughout the unit operations until the corresponding material is processed. These concepts, related to geometallurgy, mine to mill tracking, and reconciliation, are not new. Geometallurgy relies predominantly on mineralogy and intergrowth analysis from small datasets [1,13,14]. The novelty of the proposed concept is that routinely acquired material attributes are taken without making a (direct) interpretation. For example, mineralogical data will not be interpreted in terms of spectral endmembers. They will be analysed based on features including the noise and reflectance by a machine learning model. Eventually, this concept could eliminate the necessity for offline analysis and bulk metallurgical test work.

An overview of the concept can be seen in Figure 1. The physical state of material (intact, mixed, blended, responsive) changes at different unit steps of the mining cycle. However, when the material attribute classes (fingerprints) at each unit step are fully known, then the initially generated data give confidence about understanding the root cause(s) of changing performance in mineral processing. The concept methodology gives insight into upgrading the confidence degree, as well as the understanding of the material composition at various stages during the mining cycle. Implementation would allow for controlling the performance variability over time and continuous validation of the identified and measured material classes.

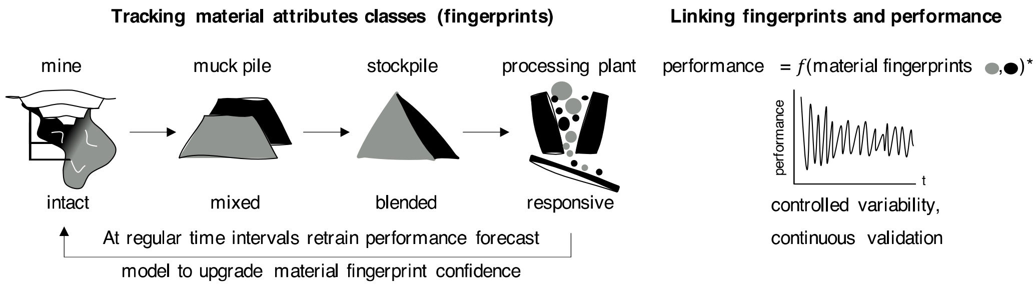

Figure 1. Concept of material fingerprints. Material attribute classes (fingerprints) can be tracked through the unit operations of a mining cycle and indicate the performance of processing them. Regular revision of the material fingerprint confidence over time (feedback loop) allows for controlling the performance variability and continuous validation. * Neglecting the changing process unit operating conditions.

The concept can be developed through the use of a self-learning system, which could learn to forecast the performance of mineral processing based on so-called material "fingerprints". This system is self-learning because it uses a learning feedback loop where forecasts are assessed against the actual performance and are used to upgrade the fingerprint confidence. Regular revision has the potential to be automated and involves retraining the performance forecast model given the additional data. A revision could be triggered at different time moments and may be based on the throughput of the processing plant and the (in)homogeneity of an orebody. The revision frequency is, therefore, operation-specific. Historical data will be kept and, depending on the spatial variability in the ore body, selective data batches can be used to converge the model to reality and forecast the processing performance. The three requisites that help to better link material fingerprints with the processing performance are as follows:

- Fingerprint definition (Section 2.1): development of ML tools which fuse data originating from various sensor responses together to form initial material fingerprints. The initial fingerprints are obtained by means of an unsupervised ML framework (i.e., clustering of the fused data), and the results are assessed for usefulness. Iteratively upgrading the initial fingerprints classification with new data gives improved confidence and higher fidelity in the characterisation of new material fingerprints. Revision may be done with supervised ML techniques (i.e., neural networks).
- Fingerprint tracking (Section 2.2): following the fingerprints throughout the unit processes of mining and identifying the change in the confidence of the fingerprint. This insight provides the means to identify and tackle material knowledge gaps.
- Model development (Section 2.3): construction of a second ML model which maps selected fingerprints to the performance of mineral processing. The selected input fingerprints for this model are fingerprints of blends and are, for example, composed of many smaller fingerprints identified during grade control mapping. If these blend fingerprints (input) match the sampling frequency of the performance of mineral processing, i.e., the output (e.g., specified by the particular operation), then they can function as input and output of a training dataset of the ML model. Semi/near-real-time mapping allows upgrading the blending or compositing strategy for the classes to maximise the performance of mineral processing.

The sections below provide details on exploiting these requisites and serve as a foundation for understanding how differences in geology impact metallurgical plant performance.

2.1. Material Fingerprints

Currently, many material attributes are measured to characterise the material and classify ore or waste types. The chemical bonding or individual elements that the material is composed of cause the main differences between different material types. The way that those elements are formed and bonded together depending on the structure gives different minerals. The combination of these particular minerals gives rocks, and various combinations of rocks or lithologies give ore or waste [15]. This composition of one sample by its material attributes is represented by the pathways (lines) in Figure 2 and shows how *n* samples are separated into three different material types (1, 2, 3). The white circles represent the presence of a measured elemental concentration of the samples (e.g., Al, Na, Au, Mg), found minerals (e.g., biotite, chalcopyrite), rock classification (e.g., granite, dolerite), or physical properties (e.g., shape, hardness, grain size). Pathways of the same colour represent how one material type has different constitutive attributes which could characterise this material type and distinguish it from others. Therefore, different material types can be characterised by combinations of attributes, and all available attributes are not necessarily needed to identify a material type. For instance, the absence of a considerable Au concentration helps to classify waste material and, therefore, such a sample does not necessarily need further analysis of the rock and physical properties.

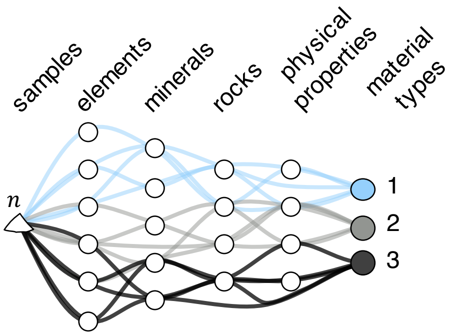

Figure 2. Conceptual diagram of material characterisation. Samples are composed of chemical elements and form into specific minerals, which form rocks or lithologies and have unique physical properties. The absence, presence, or combination of these attributes helps to distinguish material types. Colours are used for discrimination of possible pathways to characterise material types.

The traditional view of measuring and (subjectively) interpreting individual material attributes to classify material is not sufficient anymore. Alternatively, the geochemical, mineralogical, lithological, or physical signatures of samples can be found through unsupervised learning techniques (i.e., clustering). A clustering algorithm may cluster similar signatures together and could, therefore, be used to form initial material fingerprints. A (material) fingerprint is defined as a classification of the measured and constitutive material attributes compared to the range of material attributes found within an exploration area or defined using available mineral resources or reserves. An ML framework to obtain fingerprints through unsupervised learning is shown in Figure 3a. The framework starts with case-specific data preparation and selection (e.g., collecting, cleaning, feature engineering). For more information on this step, the reader is referred to References [11,16]. The result is a dataset with as many features as available for its constitutive samples and with no missing data. This dataset functions as input for an unsupervised learning model, whose output is a label for each input sample. In the case of a clustering algorithm, this will be the cluster label where the sample is assigned to and could provide multiple output cluster labels. In this case, five clusters are identified (labelled A–E). Extracting meaningful clusters useful for a specific application is not trivial and requires cluster verification through human decision-making [16,17]. Eventually, different proportions of clusters or classes (Figure 3b) will be equivalent to the various ore and waste types. This proportionality is useful for the design of blending rules and is possible because proportions (or classes) are additive, whereas individual attributes are not.

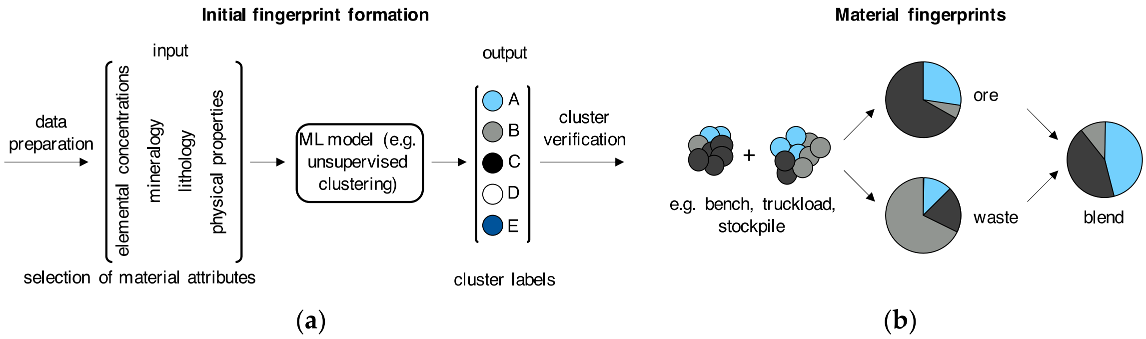

Figure 3. (**a**) An example where initial fingerprint formation is done through unsupervised clustering. Clustering generates potential cluster or class labels and may act as training data input for another machine learning (ML) model which can characterise new fingerprints from measured material attributes; (**b**) An example where three (A, B, C) class outputs are used to explain proportionality of classes. The proportionality of classes allows the formation of fingerprints which characterise ore, waste, or blend types.

In the unsupervised clustering model, related processing information of the samples is not included, because that information will only be included after the fingerprint classes are defined (see also Section 2.3). Furthermore, material properties directly related to the processing behaviour, such as work index or reagent consumption, are not collected in large quantities. ML models, on the one hand, require very large and human-labelled datasets, which unfortunately are not always available. On the other hand, many mining companies have a lot of exploration or grade control data available, which can be employed.

The following example uses ML and fused data to illustrate the formation of initial fingerprints and the creation of a labelled dataset. The example uses samples with only assay (e.g., multi-element digestion or X-ray fluorescence (XRF)), hardness, and density data to build fingerprints, and it requires data preparation. The author of Reference [18] showed an example of multi-element data preparation through cleaning, levelling, and transformation, and then used the data for a clustering analysis which helped to interpret regional geochemical survey data. After data preparation, the data serve as inputs for an unsupervised clustering algorithm in which classification is done through the extraction of the non-linear feature combinations of the data. After cluster verification, the outcome of the classification acts as a class label for a subsequent ML model and contains the relevant information that has the potential to identify the root cause of measured differences in processing behaviour. The ability to discriminate the root cause may be limited by the ability to find classes, maximise the across-class variability, minimise the within-class variability, and connect classes with the root causes. In addition, differences in processing behaviour may be due to different processing conditions and not only material attributes. However, the techniques are proposed as a valid alternative for the likely identification of the root cause. Thus, this class label can forecast the associated behaviour of mineral processing. On this basis, a fingerprint belongs to a class, and, within each class, there is a range of metallurgical properties. As a result, another machine learning model can be trained with new mineralogical data (from the same samples) as input and the fingerprint class labels as expected output. After training, this model can characterise new fingerprints from measured mineralogical data of other samples.

2.1.1. Fingerprint Confidence

Due to the ease of collecting vast quantities of data in different types and formats, care should be taken in the selection of the data for fingerprint classification. Furthermore, the choice of the kind of sensor data depends on valuable discoverable features in the sensor response data. Examples of usages and caveats of data are as follows:

- Subjective geological interpretations.

- Hyperspectral images with specific properties like colour, edges, and shapes can be used for determining textures and mineralogy, but this approach is data-intensive and sometimes complex to interpret.
- The detection limits of element concentrations measured using specific geochemical analytical techniques.
- Down-hole geophysics is used primarily for interpretations of homogeneity and bulk properties, but not for forward prediction of material attributes.

Due to differences in the nature of each technique and resulting dataset, the degree of confidence of the data is also different. Therefore, a new approach to quantify the confidence of data used for ML could help. This approach arises when the confidence is linked with the mineral reserve and mineral resource category terms from, for example, the Joint Ore Reserves Committee (JORC) code or NI43-101 [19,20]. This way, five different terms are available to describe a proxy of the confidence in data used for ML. The inferred, indicated, measured, probable, and proven terms will quantify the quality of different datasets and the understanding of material representations (fingerprints). The terminology is used because such terminology is commonly used and accepted by resource/reserve practitioners and will assist in visualising and appreciation of data quality. The goal is to increase confidence and to understand the type of material before mining commences by understanding the material. Explanations of the degree of confidence (in increasing order) in the context of this paper can be expressed as found in Table 1.

Table 1. Terminology on the degree of confidence of data.

Confidence Degree		Description
Low	Inferred	Inferring of properties through proxies is needed.
↓	Indicated	Good indication of what the data or material encompass(es).
	Measured	Provision of an exact measured result, but without much representation, i.e., not that useful yet.
	Probable	Reliable indication or representation (measured), and more information can be derived from the data.
High	Proven	Exact measured results which directly provide additional information.

Care should be taken to not directly link the degrees of confidence to formal resources or reserve classifications. In general, this proposed concept would apply to a mining operation and, therefore, all material would be classified as a reserve. Based on this concept, Figure 4 shows the degree of confidence for selected datasets. The datasets are combined in classes of mineralogical, geochemical, (geo)physical, or combinatorial identification datasets. The confidence consists of a box and its representative colour.

The ranges are based on confidence in the quality, quantitative nature, robustness, and representativity of the data. The box colour is based on two things: (1) the added value of this data to an already existing fingerprint classification, and (2) the type of information that is useful for predicting the behaviour of mineral processing. The added value of a dataset may be high and recommended, average, or low. For example, X-ray diffraction (XRD) measurements are done on a relatively small sample with time-consuming sample preparation. Afterwards, it is possible to infer properties (quantitative mineralogical interpretations) for particular minerals via Rietveld analysis [21]. Therefore, XRD datasets resemble an inferred degree of confidence. A single infrared or XRF dataset will only give inferred or indicated material properties. Although the samples are measured with high precision, their representative spot size is small. Moreover, further interpretation of the spectra is necessary to make use of the result. Nevertheless, adding an infrared or XRF dataset to a fingerprint built based upon a multi-element and core logging dataset (of proven confidence) adds value. This could, for example, show the lines between geochemistry and mineralogy, because the given elemental concentrations from multi-element analysis relate to the minerals found within the XRF results (the minerals are composed of these elements).

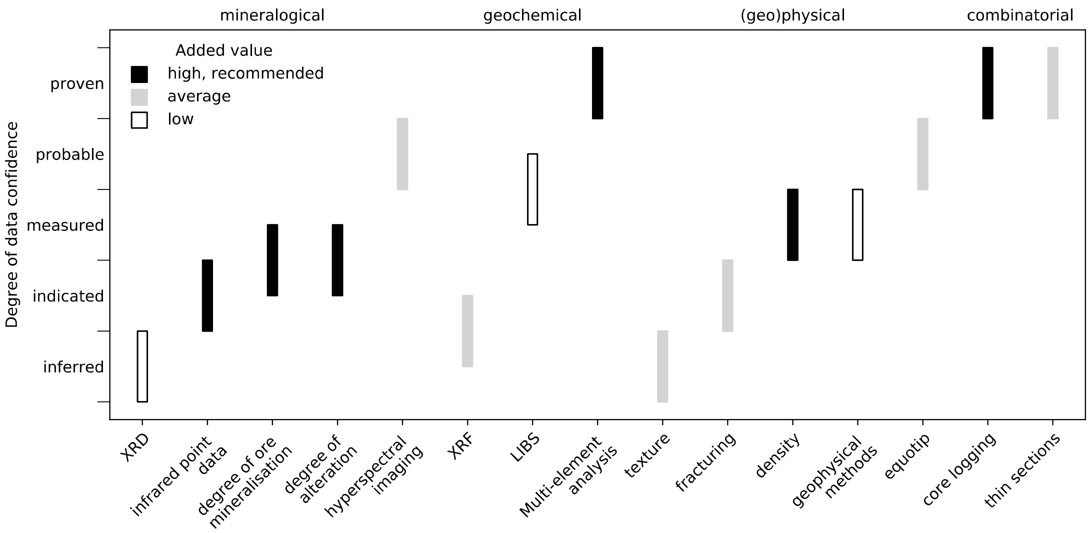

Figure 4. Indicative ranges of dataset-specific confidence in the quality, quantitative nature, robustness, and representativity. The box colour is based on added value to the fingerprint classification.

2.1.2. Sequential Increase of Confidence

In theory, all types of data can be used for a fingerprint, but different aspects such as the precision, accuracy, resolution, and sensitivity of the data should be considered. For the fingerprint classification, it is not necessary to always interpret the individual data sources for the goal of understanding and, therefore, data fusion should cover two aspects. Firstly, it should increase the confidence in the data, which represents the material attributes; additionally, it should converge this confidence to a reality. This way, it increases the indirect confidence of an inferred analytical technique, as well as the degree of fingerprint confidence. Secondly, doing sequential measurements with an inferred analytical device should provide the same confidence and enhances the inferred data source to a measured data source (feedback loop in Figure 1). Once a successful fingerprint classifier is in place, it is possible to measure a fingerprint with one sensor and know the related behaviour of mineral processing. For example, suppose that multi-element data are used to classify the fingerprint classes (unsupervised clustering), and an ML model is trained with mineralogical data (infrared) and the multi-element class labels. If the fingerprint classes are explored for processing behaviour, then, from a new infrared measurement, it is possible to get a proxy for the processing behaviour.

Please note that the suggested confidence classifications in Figures 4 and 6 are only based on the experience of the authors with the selected datasets and mining operations.

2.2. Tracking of Fingerprints

During mineral exploration programmes, degrees of confidence are given to classify resources and reserves. The goal is to increase confidence and to understand the type of material before mining commences, whereas, during mining, this exploration paradigm is inverted, because relocating material causes the material knowledge to lose, which decreases the confidence. During each process of the mining cycle, the fingerprint confidence can be determined, as elaborated on in Section 3. The loss of confidence can be solved by material tracking as it provides the means to follow the material fingerprints and confidence loss during mining.

A proposed material tracking system would benefit from a particle breakage model, such as that described by Reference [4], to describe inheriting features from big to smaller rocks (particles). This model should be combined with a commercial production machine tracking software [22,23] to enable the following of fingerprints throughout the unit operations of a mining cycle. With such models in place, it is possible to identify locations where there is a gap in the understanding of the fingerprint composition. Such a gap is present, for example, when tracking material in stockpiles and understanding the blending of fingerprints. The way that ore is added to stockpiles does not correspond to the way that ore is reclaimed from the stockpile. An addition/reclamation model of a stockpile, which tracks the material through the stockpile, could give a better overview of the material flow. In addition, at locations with a gap (e.g., a blasted bench, truck, stockpiles), it is possible to do new measurements with appropriate sensors (e.g., hyperspectral imaging or RFID tags (radio frequency identification) [13,24]) and consequently increase the fingerprint confidence, which ultimately improves the forecast of the processing behaviour.

Considering the development of a reserve model, the origin of a fingerprint is within the smallest mining unit (SMU) of a block model. At this stage, a fingerprint is a collection of the estimated block parameters related to the spatial position. As soon as drilling commences within this block, new material attributes are obtained. Therefore, it should be possible to modify the fingerprint with new parameters and ask for a hybrid character. Implementation of the hybrid character can be seen in Figure 5. During reallocation of the material, this hybrid character also allows the fingerprint to break down into smaller pieces, which then form fingerprints again. For each of the fingerprints, it is possible to classify and predict the processing behaviour (Section 2.3), thereby allowing for better decision-making regarding the material allocation, blending strategies, or processing settings. If there is a subsequent unit process, then this can be used to update the fingerprint data attributes again.

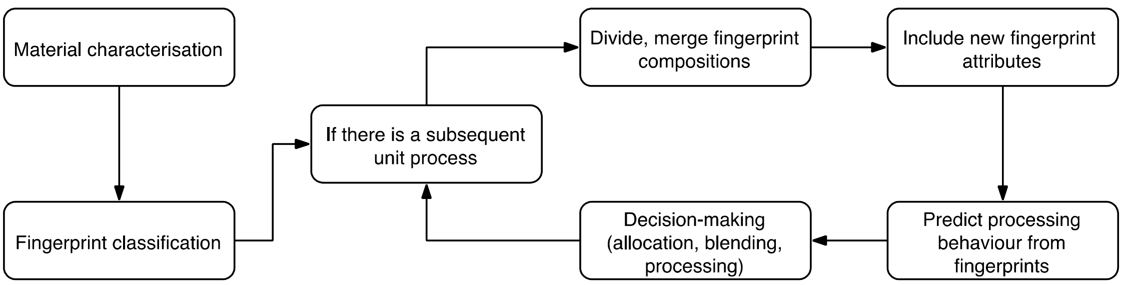

Figure 5. Flowsheet on how the hybrid fingerprint character allows for changes in the fingerprint composition during the unit processes of a mine and allows for better decision-making.

2.3. Model Development

A second ML model can make predictions of equipment performance parameters from the fingerprint of a scheduled blend. Therefore, a fingerprint obtains its full potential when it does not represent one class of material, but rather a blend of classes. Here, the proportionality of classes plays an essential role (Figure 3b). The input of the model consists of different fingerprint class proportions, and construction of the ML model training dataset is done in two steps. Step one is finding the performance indicators for different (pure) classes and simple class proportions. Step two may find relationships with varying proportions considering all classes from historical data.

To further illustrate the primary purpose of the ML model, the example described below uses the throughput of the ball mill and shows the construction of the training dataset from step one. The effect of changing process unit operating conditions such as the effect of mill liner wear on the processing performance is not considered at this stage. Appropriate breakage tests could provide initial class throughput predictions of the different fingerprint classes and simple fingerprint class proportions (e.g., 50% class A and 50% class B). These properties can, for example, be derived from Bond ball work index tests, JK drop-weight tests, or SMC tests® from representative diamond drill core samples [5,25]. These fingerprint labels then represent the throughput or, more generally, the comminution properties such as the grinding power required for a given throughput of material under ball mill grinding conditions. As a result, the ML model can predict the throughput (output) from the (simple) input fingerprints. These input fingerprints may be single-class fingerprints or combinations of fingerprints in different proportions. This output directly reflects how the ball mill would perform by processing this material.

However, it is impossible to do breakage tests for all possible class proportionalities and, therefore, additional proportional relationships between blend fingerprints and the actual ball mill response can be found from either historical or actual performance data. Following this, as step two, these data can be added as additional training data to improve the previous model. Adding the historical data is possible if the fingerprints of the plant feed material (with proportions of classes) can be reconstructed and if the associated measured performance data are available. In cases where such data are not available, then the fingerprint classes of the to-be-processed plant feed and actual performance data could be used. These two data sources should reveal similar links between the fingerprint and associated behaviour of processing, from which a model should be able to make operational predictions. This can be done when the material fingerprint of a scheduled blend functions as an input of a trained model, which outputs the predicted equipment performance. These prediction forecasts will improve if, at regular intervals, the model is retrained (feedback loop) with new fingerprints and actual performance labels.

The secondary purpose of the ML model is to allow for a retrospective and iterative confidence upgrade. The upgrade goes from the inferred to the measured and back again to the proven fingerprints. This can be done with this last feedback loop by comparing the predicted versus the actual performance. This can be achieved as described in the framework of Reference [3]. Moreover, upgrading the blending or compositing strategy for classes is key to maximising mill performance and minimising environmental footprint.

3. Case Study

After the formation of fingerprints, they can be used for prediction of the processing behaviour as they incorporate all available chemical, mineralogical, and physical attributes. As discussed in Section 2.1.1, the confidence of fingerprints obtained after the ML approaches is determined by the confidence of the datasets used to generate them. Adding more attributes would generally increase the fingerprint confidence. Additional effects which affect the fingerprint confidence are related to whether they were obtained through direct measurements or through proxies, and whether the input dataset was single-variate or multivariate. To further illustrate the usefulness of fingerprints in mining, this section describes a case study. The case study shows the application of using fingerprints and its associated confidence degree in an open-pit mining operation.

The emphasis is on describing the type of available data in each unit process of a mining cycle, as well as on the impact of different processes on fingerprint confidence. The goal is to show how the degree of confidence of fingerprints plays a key role during a mining operation. Figure 6 shows, for each unit process, indicative estimations of the expected degree of the fingerprint confidence and the cumulative number of data points, which describe the fingerprint attributes. A confidence region (coloured shaded area) indicates the degree of confidence, and it increases or contracts in height based on the confidence at each unit process and optimality scenario. A suboptimal and an optimal scenario are shown in Figure 6. The difference in these scenarios results from the capability of incorporating sensing techniques. Here, optimal refers to a scenario where the mine minimises energy consumption and maximises recovery by understanding the material fingerprints. On the other hand, a suboptimal scenario relates to a limited use or acquisition of sensor data to understand material attributes. The confidence degrees of the suboptimal and optimal scenario may overlap with each other.

The paragraphs below describe, for each of the unit processes from Figure 6, how the indicative estimation of the degree of confidence in the fingerprint and the cumulative number of available data attributes are derived.

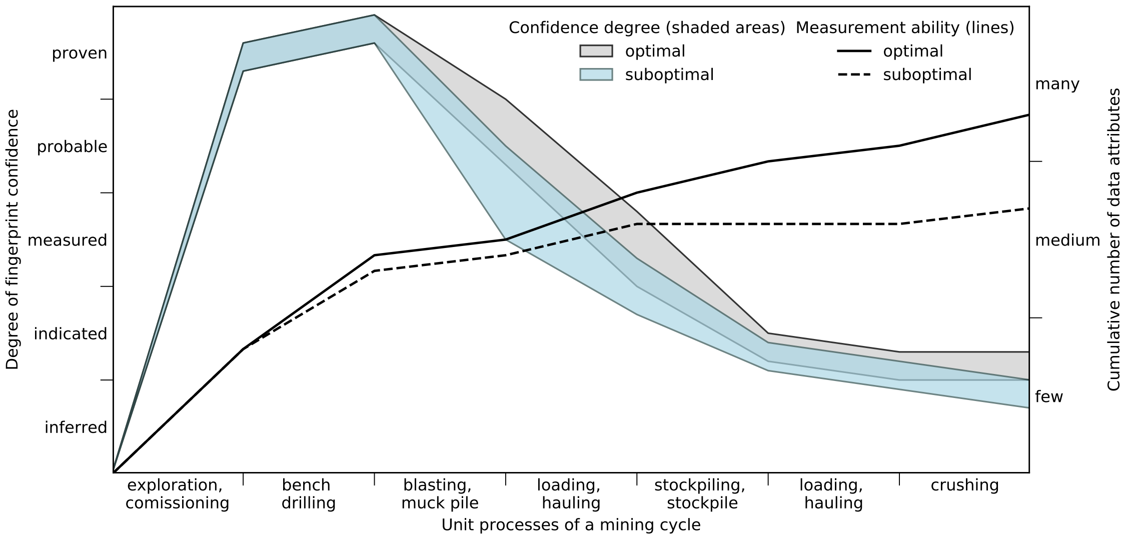

Figure 6. Indicative estimation of the degree of confidence in the fingerprint and the cumulative number of available data attributes throughout the mining cycle for two scenarios. The difference can be found in the degree of optimality and relates to the capability of incorporating sensing techniques.

Exploration, commissioning: The goal during exploration and commissioning of a mine is to define proven fingerprints. This is done by collecting as many material attributes as possible to classify the material as proven reserves, which will be mined out. Therefore, the fingerprint confidence at this stage increases from no confidence to a proven degree of fingerprint confidence. This is also the starting point of the mining operation and the first time the fingerprint is defined. Most of the black highlighted datasets from Figure 4 are collected before mining commences, and they give a basic amount of material attributes.

Bench drilling: Grade control drilling allows for indirect measurement of the defined proven fingerprints and, therefore, increases the confidence and number of attributes. Rock chips are usually analysed using an infrared device, which gives new inferred mineralogical data and increases the fingerprint confidence. For example, a dense 6×6 m drilling pattern gives, for each 5-m composite per hole, one infrared measurement. A $120 \times 60 \times 10$ m bench then provides 400 additional infrared spectra. Depending on the analytical methods in place, the mineralogy can easily be added as an attribute to the fingerprints.

Blasting, muck pile: Blasting decreases the fingerprint confidence towards the probable and measured degree of confidence. The reason is that the material is fragmented, mixed, and diluted across grade boundaries. However, the confidence loss can be limited by optimised blast processes for different rock types. Additional muck pile modelling could account for the blast movements and tell the approximate material location. It should be mentioned that, if the blast design or analysis is incorrect, the confidence will steepen more rapidly. Since the muck pile is the direct result of blasting, it will show the effectiveness of the blast and always give additional data.

Loading, hauling between muck pile and stockpile: Loading and hauling is an essential process in determining the fingerprint confidence for two reasons. Firstly, a loader or excavator picks up individual measured small fingerprints, where unavoidable mixing of fingerprints takes place. Therefore, it is essential to rely on a good classification of the material. Secondly, proper allocation of the material increases the chance of having uniform stockpile compositions with one blend of material (with one known blend fingerprint composition). Depending on the allocation and the ability to track the material, the degree of fingerprint confidence decreases towards a measured confidence as the material is still known. However, there is more significant uncertainty in the exact location. The ability to decide on the dispatch location of the material increases the number of data attributes.

Stockpiling, stockpile: Typically, stockpiles are built up from different types of material, and mixing of material takes place during stockpiling. Therefore, the fingerprint confidence decreases and only a good indication of where a fingerprint is situated is possible. However, from the fingerprints of stockpiles, it is known that the material is mainly ore and, therefore, the confidence spread decreases. Stockpile sampling gives new fingerprint attributes and, for example, additional XRF analysis or hyperspectral imaging could quickly endorse the fingerprint compositions.

Loading, hauling between stockpile and primary crusher: Fingerprints resemble blends of material at the stockpile and, therefore, reclaiming this material does not decrease the confidence much. The cumulative number of attributes increases because the reclamation source and time, the time of delivery to the crusher, and the blend composition which determines the behaviour of processing are known. Therefore, keeping track of the material fingerprints related to feeding of the primary crusher is an important step and allows for linking the processing behaviour with the last known fingerprint.

Crushing: In the primary crusher, the material is diluted if it originates from different stockpiles. Hence, the fingerprint confidence decreases. If the feed is from one stockpile, the confidence will remain the same. Summing up all the previous unit process steps shows that the confidence of the composition of the material that goes into the grinding circuit is at the inferred degree. However, if the expected fingerprint is linked with the processing behaviour data, then the knowledge about a fingerprint increases significantly.

Commodity-Specific Examples

Mines exploiting different commodities utilise similar unit processes, but the complexity of these unit processes changes due to different geological conditions. Three examples of various commodities with their related differences in the confidence of fingerprints are as follows:

- High-quality **iron ore** may be possible to distinguish from waste material based on colour and could increase the confidence in the selection of material for the stockpiles. Usually, the key factor in mining iron ore is strongly related to the quality (penalty elements) rather than the grade. Furthermore, iron ore characterisation can rely on the hyperspectral features and magnetic susceptibility of iron-bearing minerals [26]. This might provide valuable attributes not further relevant to other commodities. Magnetic susceptibility measurements at the muck pile, loaders, trucks, or stockpile would provide valuable extra fingerprint attributes.
- Porphyry **copper ore,** similar to iron ore, is mined in large-scale mining operations. However, the copper grade is usually very low and, thus, lots of gangue material must be mined. If more confidence is obtained in characterising fingerprints that represent the higher-grade material, more efficient operations can be made. For example, the alteration minerals associated with porphyry copper deposits have characteristic infrared spectral features [27] and could be used to link the behaviour of copper processing with fingerprints.
- Open-pit **gold** mining operations usually entail mining abundant gangue material for a relatively small amount of gold. However, most of the material that is processed will contain some gold and can be extracted. High-grade material can be identified when the typical alteration associated minerals related to, for example, gold veins are found. Then, these alteration minerals can be detected with different techniques and be an indicator of the material [10]. Thus, better characterisation of ore fingerprints reduces the amount of waste processing and, additionally, minimises the environmental footprint.

4. Discussion

In modern operations with vast quantities of accessible and clean managed data, there is a large potential value. The data fusion should be preferentially using high-confidence data so that proven fingerprints can be obtained. The creation of fingerprints could, for example, rely on high-dimensional clustering of apparently unrelated features. Afterwards, these fingerprints can be linked with the processing behaviour through neural networks. However, it remains to be seen how effectively the concept of fingerprints can be applied retrospectively to existing or old mines. In particular, when there are already large stockpiles or waste dumps, or the data are inaccessible, in the wrong format, or lacking in quantity/representativity, then this approach might not be beneficial.

The applicability of fingerprints could also substitute and reinforce expensive metallurgical tests. For example, if core samples with representative fingerprints are tested, then these results may better resemble the behaviour of processing compared to a limited number of metallurgical bulk samples (not considering changing process unit operating conditions). In addition, a mill needs to be designed to handle the hardest material from the ore reserves, although that is only a small portion of the ore. Therefore, instead of changing the physics of the mill to process this material better, the fingerprints can be relied on, which better represent all material. An understanding of the fingerprints could permit an optimal blending and feeding strategy. For this blend, the potential recovery is known and, therefore, the required feed rate for achieving it.

There is a significant drop in the fingerprint confidence between the moment of mining and processing. Tracking of fingerprints and having the ability to measure them allows for lowering this drop as the confidence can be upgraded through the feedback loop. The implementation of the feedback loop also allows for real-time reconciliation of material grades against fingerprint estimates and a recalibration of the fingerprint classifiers.

Fingerprints allow an operation to identify material through the process, regardless of resembling a block model's block, truckload, stockpile, or mill feed. Therefore, their use can also be extended towards flotation and (pyro)metallurgy. In particular, in confined and controlled conditions, like flotation, their use enables understanding the occurring physical and chemical mechanics and the produced type of waste or tailings. Moreover, the capacity to decide the composite of the blend gives the ability to produce customised (or zero) waste.

5. Conclusions

This paper introduced a conceptual framework where fingerprints derived from machine learning are used as a tool for linking material attributes and blend composition with the expected and obtained behaviour of processing. Defining fingerprints from high-confidence-based data and having the ability to measure and then track them throughout the unit operations of a mine gives confidence in the use and ability of fingerprints. Eventually, having an increase in confidence allows for optimising the behaviour of mineral processing. Fingerprints are built up using the fusion of vast quantities of data acquired during material characterisation, and they may be found through unsupervised clustering. Therefore, insight was given into the usefulness of these different datasets and into how well fingerprints characterise the material at each step of the unit processes of mining. The descriptive case study showed that the confidence degree of the composition of the material that enters into the primary crusher is inferred. In practice, this means that it is not understood what the material composition (or blend) is. By means of material tracking and a feedback loop for upgrading the degree of fingerprint confidence, this confidence can be increased towards a measured and, eventually, a proven fingerprint. A proven fingerprint can directly reflect the expected processing behaviour, improve the recovery, and reduce the amount of waste. Successful implementation gives retrospective value to all the collected data and could be useful in many operations.

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